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Optimized plastic injection molding process and minimized the warpage and volume shrinkage by response surface methodology with genetic algorithm and firefly algorithm techniques

Supattarachai Sudsawat & Wipoo Sriseubsai*

Department of Industrial Engineering, Faculty of Engineering, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand

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This goal of this paper is an optimization approach to generate suitable process setting of multi responses of the minimization of warpage and volume shrinkage in the plastic injection molding (PIM). Central composite design (CCD) was employed to handle the orthogonal array for experimental test runs and using the response surface methodology (RSM) to construct response surface equation model. Then the optimization methods of firefly algorithm (FA) that have never been applied to minimize warpage and volume shrinkage in the plastic injection molding (PIM) and genetic algorithm (GA) were employed to optimal parameter conditions with fitness function generated from RSM. Simulation software Moldex 3D and plastic injection machine were used as the experimental tests to show the comparison of the optimal performance of both metaheuristic algorithms. The results showed that the firefly algorithm created the suitable process parameters to meet the minimization of warpage and volume shrinkage better than the popular genetic algorithm for this study. It can be concluded that FA is very proper to approach the good performance in PIM.

Keywords: Plastic injection molding (PIM), Response surface methodology (RSM), Genetic algorithm (GA), Firefly algorithm (FA), Moldex 3D simulation

Nowadays, plastic injection molding (PIM) is used to form the major part in many areas of industry because it can easily meet various requirements such as the wide variation of geometry, low unit cost to produce compared with others, short production cycle time, and perfect surface quality of the products. Therefore, for these reasons it is not surprising that PIM has been mainly used to produce plastic products. In PIM process, loss during the operation is an obstacle that may lead to a tendency of higher product cycle time, cost, and dissatisfied customers. Warpage and volume shrinkage are among the most significant defects. The intensity of these losses is highly involved with the parameter setting in the injection molding operation[1].

Many researchers studied, and recommended the method to avoid an occurrence of warpage and volume shrinkage based on the finite volume analysis method, computer-aided engineering (CAE) simulation, and practical experiments[2]. Chaing and Chang[1] investigated the relationship between shrinkage and warpage in injection-molded parts via various process parameters being mold temperature, packing time, packing pressure and cooling time. It was found that mold temperature was significant.

The volume shrinkage was increased as the mold temperature increased, and the mold temperature range from 45°C to 55°C was suitable or minimum warpage values, but the velocity injection was not considered. Zhao *et al.*[3] did a study of the correlation of warpage, shrinkage, and sink marks. The research result could indicate that warpage and shrinkage were significant trade-off, whereas warpage and sink index or shrinkage and sink index were not both significant trade-off. Santos *et al.*[4] tried to improve the volume shrinkage and warpage problems of polymeric composite reinforced by using short natural fibers. The results found that the short natural fiber can continually decrease the problems as the percentage of short natural fiber increases, but this research did not pay attention to the process parameters in PIM. Chiang *et al.*[5] researched the minimization of warpage by using material test between acrylonitrile-butadiene styrene (ABS) and polycarbonate (PC)+ABS based on process conditions such as melt temperature, injection speed, and packing pressure. The results found that

*Corresponding author (Email: wipoo.sr@kmitl.ac.th, s.supattarachai@gmail.com)

melt temperature was the most important factor to minimize warpage and ABS was more suitable material than PC+ABS. This research could not find that mold temperature, injection pressure, packing time, and cooling time were considered. Much research employed a mathematical model to use statistical analysis and optimization methods to manage loss problems such as warpage, volume shrinkage, sink index, and short shot. The optimization techniques can mainly be classified as five techniques, namely the Taguchi technique for design of experiments, modern computational techniques, hard computing techniques, real time techniques, and soft computing techniques[6]. Zheng *et al*.[7] used the Taguchi experimental method to minimize warpage by using an L27(3^3) orthogonal array to construct experimental tests. Then there was an investigation of the process parameters such as mold temperature, melt temperature, and packing pressure, but cooling time and injection pressure were not considered. There was use of computer-aided engineering (CAE) to determine the extent of warpage. The results show the warpage value from the Taguchi method was less than the amount of warpage when there was a recommendation of process parameters. Erzurumlu and Ozcelik[8] studied the minimization of warpage and sink index by using the Taguchi optimization technique via process conditions such as mold temperature, melt temperature, packing pressure, rib cross-section types, and rib layout angles, but packing time, cooling time and other factors were not considered. The experimental result could confirm that this technique gained the minimum warpage and sink index. Lam *et al*.[9] used the modern computational techniques via Moldflow commercial simulation software to investigate the suitable process conditions. The results indicated that software could find the nearest process condition compared with the optimal result, but the cooling system was not added in the consideration. Lin and Lian[10] used self-organizing fuzzy controller (SOFC) for PIM operation by controlling injection screw velocity and injection-nozzle holding pressure. The results found that this controller can reduce the loss problems such as shrinkage and residual stress more than the controlled process with fuzzy logic controller (FLC) and the proportional-integral-derivation (PID). The soft computing technique that has been popularly used in PIM operation can be separated into three parts as artificial neural network (ANN), evolutionary algorithm (EA), and hybrid approaches[6]. Shi *et al*.[11], used the ANN to solve the warpage problem and used Moldflow Corporation's Plastics Insight software to analyze the problem. The results show the effective optimization of parameters in PIM for producing TV covers and plastic lenses as a quick approach. Guo *et al*.[2] investigated the minimization of sink mark depth via design of experiment (DOE) integrated with evolutionary algorithm (as genetic algorithm, GA) to solve the problem by considering mold temperature, packing pressure, coolant temperature, rib thickness, etc., but injection pressure was not considered. The results illustrate the good performance of minimized sink mark. Xu *et al*.[12] used another evolutionary algorithm (as particle swarm optimization, PSO) to find suitable process parameters. The results found that it was suitable for multi-objective optimization of PIM process. Hybrid approaches were also another choice for improving loss problems in PIM process. For example, Ozcelik and Erzurumlu[13] used a hybrid of neural network model and genetic algorithm to seek the warpage optimization. This algorithm can improve the warpage problem by 51%. Deng *et al*.[14] made a study of a hybrid optimization by combining a mode-pursuing sampling (MPS) and genetic algorithm to minimize the warpage of injection molded plastic parts. This approach considered mold temperature, melt temperature, injection time, and packing pressure; research results showed good performance as minimization of warpage and the time-consuming CAE simulation. Presently, soft computing techniques were widely applied in PIM process to improve process qualities as mentioned. Another soft computing technique is firefly algorithms that can afford perfectly complex nonlinear problems[15]. Yang[16] created the firefly algorithm (FA) by simulating firefly nature behavior. This algorithm was proved and compared with other metaheuristics such as genetic algorithm (GA) and particle swarm optimization (PSO). The results found that FA could give better and quicker convergence answers toward the optimality[15].

The purpose of this research was to minimize the warpage and volume shrinkage by seeking an optimization model of process parameters via metaheuristic methodology through the comparison of popular genetic algorithm and firefly algorithm to lead to better performance. Central composite design (CCD) was used to design the experiment as 84 runs. Then an example part was employed to simulation software Moldex 3D to get the simulated data. Genetic algorithm and firefly algorithm were employed to minimize warpage and volume shrinkage for plastic injection molding process (PIM) and the results of both algorithms were compared by empirical tests through injection molding machine. Finally, the direct utilization of this research work will provide appropriate parameter setting for injection molding operators.

Materials and Part

To approach the finite volume analysis, a 3D wrench model part in this study was illustrated in solidworks, as shown in Fig. 1. The dimension of this work-piece was 121.33 mm x 4.01 mm x 72.85 mm. General purpose polystyrene (GPPS) was chosen from the Moldex 3D software, and the manufacturer was CHI-MEI Co. Ltd. The material properties are presented in Table 1. The size characteristics of model part, cooling, modeling and meshing process performed by Moldex 3D shown

Fig. 1 — A 3D wrench example part

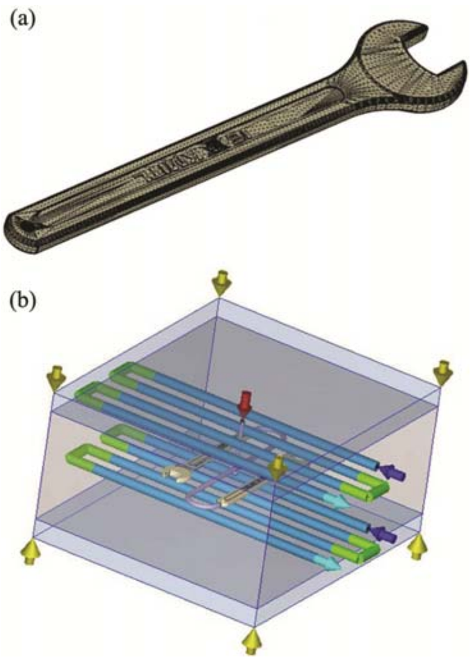

Fig. 2 — Mesh element (a) Part and cooling line (b)

in Fig. 2. The simulated model of the part consists of 191,786 elements. The pin gate and water cooling system were established in Moldex 3D software following common gate and cooling system design and creating actual injection mold shown in Fig. 3 for empirical tests.

Experimental Methodology

The research methodology can be summarized clearly as a flow chart which is illustrated in Fig. 4. The first step, experimental orthogonal array is created by central composite design (CCD), and second, the predicted model is established by

Fig. 3 — Toshiba 80T injection molding machine

Table 1 — Material properties of general purpose polystyrene (GPPS) (PG-22, CHI MEI corporation, Taiwan)

Physical Properties

Properties	Method	Unit	Value
Melt flow index (5kg/230°C)	ASTM D1238	g / 10 min	17.5
Izod impact strength (6.4mm/23°C)	ASTM D256 (Notched)	kg-cm/cm	1.4
Tensile strength at yield (6mm/min)	ASTM D638	kg/cm^2	425
Flexural strength at yield (6mm/min)	ASTM D790	kg/cm^2	540
Flexural modulus (2.8mm/min)	ASTM D790	10^4 kg/cm^2	3.1
Rockwell Hardness	ASTM D785	M-Scale	74
Heat distortion temperature (Unannealed)	ASTM D648	°C	75
Vicat softening point (1kg/50°C/h)	ASTM D1525	°C	87

Chemical properties

Chemical name	CAS number	EC number	Percent weight
Polystyrene or styrene polymer	9003-53-6	Polymer	$> 95\%$
Additives	-	-	$\leq 5\%$

Processing technique	
Ejection temperature	108°C
Processing temperature	170 – 210°C
Mold temperature	40 -70°C
Freeze temperature	117° C

response surface methodology (RSM). Then the predicted model is applied into Genetic algorithm and Firefly algorithm to seek the minimization of warpage and volume shrinkage. In the last step, the comparison of the results of both algorithms is made to find the smallest warpage and volume shrinkage through Toshiba 80T injection molding machine as shown in Fig. 3.

Central composite design of process parameters

In this research, central composite design (CCD) is used to design experimental tests run on Moldex 3D software. CCD is well known as a designer of experiment arrays to produce the quadratic model of RSM[1,17].

To indicate the effect of process parameters on warpage and volume shrinkage of PIM, the parameters in Table 2 are selected for consideration. According to the CCD design experiment method, seven factors are classified to be three levels as shown in Table 2, and consist of fourteen star points, and six central points, and α value of 1 according to Chiang and Change's research methodology[1]. Then the 84 experimental runs are established based on the CCD method as given in Table 3.

Table 2 — Processing parameters and levels

Number	Factors	Levels		
		Low	Median	High
1	Melt temperature (*A*) (°C)	170	190	210
2	Mold temperature (*B*) (°C)	40	55	70
3	Flow rate profile (*C*) (%)	10	30	50
4	Injection pressure (*D*) (%)	40	60	80
5	Packing time (*E*) (s)	1	5	10
6	Packing pressure (*F*) (%)	20	50	80
7	Cooling time (*G*) (s)	10	27.5	45

Addition: Water coolant temperature is constant as 55°C
Maximum injection and packing pressures equal to 199 Mpa following Toshiba 80T Injection molding machine specification

Creating predicted model

Before going to the optimization methodology step, the response surface methodology has to establish the nonlinear mathematical model based on polynomial equation for warpage and volume shrinkage as shown in Eqs (1) and (2), respectively.

$$W = A_0 + \sum_{i=1}^{k} A_i X_i + \sum_{i<j}^{k} A_{ij} X_i X_j + \sum_{i=1}^{k} A_{ii} X_i^2 \qquad \ldots (1)$$

$$V = B_0 + \sum_{i=1}^{k} B_i X_i + \sum_{i<j}^{k} B_{ij} X_i X_j + \sum_{i=1}^{k} B_{ii} X_i^2 \qquad \ldots (2)$$

where X_i is independent variables, W represents warpage response, V represents volume shrinkage response, k is the number of design variables, A_0 and B_0 are the coefficients of constant, A_i and B_i are the coefficients of linear, A_{ij} and B_{ij} are the coefficients of cross product term, and A_{ii} and B_{ii} are the coefficients of quadratic.

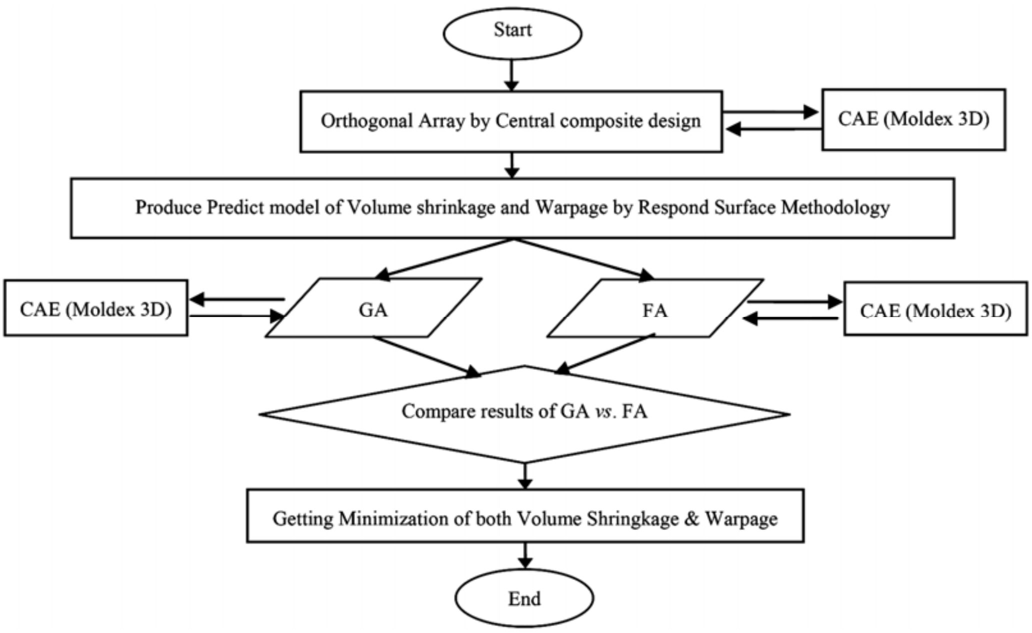

Fig. 4 — Flow chart of methodology

Genetic algorithm established

After creating predicted fitness model, GA is implemented. GA is one of the stochastic search algorithms based on natural genetic behavior. In GA, each solution is encoded, which is called a chromosome. GA will construct the initial population of chromosomes from the predicted fitness model via cost function, then crossover and mutation mechanism will be employed in the algorithm[2]. Parato-optimal solution will be selected for the best solution as shown in Fig. 5(a).

Firefly algorithm established

In the same way as GA, after gaining fitness function from RSM methodology, it will be employed to be a multi-objective function (warpage and volume shrinkage) in firefly algorithm (FA). Firstly FA creates the initial population of *n* fireflies as represented in the search space of solutions and sets parameters of the attractiveness, light absorption coefficient, and randomization factor. Then the evaluate fitness is employed by calculating the intensity, relative brightness, and attraction and next the best fitness through firefly algorithm is ranked[15]. Then the methodology provides the best solution of minimization of warpage and shrinkage. The flow chart of the algorithm is shown in Fig. 5(b).

Optimal model

Optimized plastic injection parameters and minimized the warpage and volume shrinkage can be stated in Eq. (3) and Eq. (4) respectively.

$$\text{Find } X=[A,B,C,D,E,F,G] \quad \ldots (3)$$

$$\textit{Minimize}\, f(X)=W \text{ and } f(X)=V \quad \ldots (4)$$

$$\text{Subject to}: 170\le A\le 210\le {}^{\circ}\text{C}, 40\le B\le 70^{\circ}\text{C}$$

$$1\le C\le 50\%, 40\le D\le 80\%$$

$$1\le E\le 10\text{s}, 20\le F\le 80\%$$

$$10\le \text{G}\le 45\text{s}$$

Based on 199 MPa maximum of both injection and packing pressures following Toshiba 80T Injection molding machine specification, *f*(*X*) represents the quantified warpage and volume shrinkage of the experimental part.

Results and Discussion

RSM through CCD method

The 84 experimental tests were established according to CCD method. Table 3 shows the results based on Moldex 3D simulation. Then this result was used to create the predicted models of warpage and

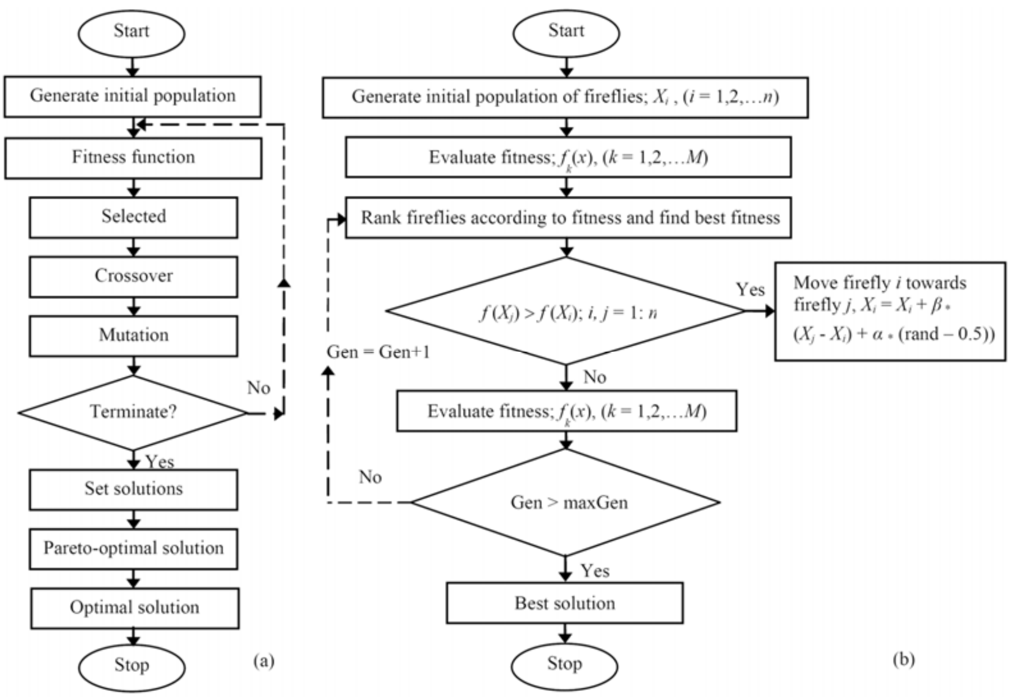

Fig. 5 — Flow chart of multi-objective grouping genetic algorithm (a) and multi-objective firefly algorithm (b)

Table 3 — Design and result of central composite design experiments

No.	*A*	*B*	*C*	*D*	*E*	*F*	*G*	Volume shrinkage (%)	Warpage (mm)
1	170	40	10	40	1	60	10	5.497	0.573
2	170	40	50	40	5	60	10	4.953	0.522
3	190	70	30	60	3	45	21	4.382	0.485
4	190	55	30	60	5	45	21	4.102	0.473
5	210	40	50	80	1	60	32	4.055	0.528
6	170	70	50	80	1	30	10	5.472	0.569
7	170	70	50	80	5	60	10	4.953	0.522
8	190	55	10	60	3	45	21	4.383	0.485
9	190	55	30	60	1	45	21	4.668	0.496
10	170	70	50	40	5	30	10	4.907	0.514
11	170	70	10	80	5	60	32	2.852	0.444
12	170	70	10	40	5	60	10	4.953	0.522
13	210	55	30	60	3	45	21	5.219	0.551
14	190	55	30	60	3	45	21	4.383	0.485
15	170	70	10	80	1	60	10	5.497	0.573
16	210	40	10	40	1	30	10	7.189	0.704
17	210	70	10	40	1	60	10	7.206	0.707
18	210	70	10	40	5	60	32	3.622	0.516
19	190	55	30	80	3	45	21	4.383	0.485
20	190	55	30	60	3	45	21	4.383	0.485
21	190	55	30	60	3	60	21	4.398	0.487
22	190	55	30	40	3	45	21	4.383	0.485
23	210	40	10	80	5	60	32	3.623	0.516
24	170	40	10	80	5	60	10	4.953	0.522
25	170	70	50	40	1	60	10	5.497	0.573
26	190	55	30	60	3	45	21	4.383	0.485
27	170	70	10	80	5	30	10	4.907	0.514
28	210	70	10	80	5	60	10	6.546	0.618
29	210	40	50	80	5	60	10	6.546	0.618
30	210	40	10	80	1	30	32	4.045	0.526
31	210	40	10	80	1	60	10	7.206	0.707
32	170	40	10	80	5	30	32	2.809	0.436
33	210	70	10	40	1	30	32	4.044	0.526
34	210	70	10	80	5	30	32	3.612	0.514
35	170	70	50	40	5	60	32	2.852	0.444
36	210	70	50	80	1	30	32	4.044	0.526
37	190	55	30	60	3	45	21	4.383	0.485
38	170	70	10	40	1	30	10	5.472	0.569
39	170	70	10	80	1	30	32	3.002	0.454
40	210	70	50	40	5	60	10	6.546	0.618
41	170	70	50	80	1	60	32	3.021	0.457
42	190	55	30	60	3	45	21	4.383	0.485
43	210	70	50	40	1	60	32	4.055	0.528
44	170	40	50	80	1	60	10	5.497	0.573
45	210	70	50	80	5	30	10	6.526	0.616
46	170	40	10	40	1	30	32	3.003	0.454
47	190	40	30	60	3	45	21	4.382	0.485
48	210	70	50	80	5	60	32	3.622	0.516
49	210	70	10	40	5	30	10	6.526	0.616
50	210	40	50	80	5	30	32	3.613	0.514
51	170	40	50	80	5	30	10	4.907	0.514
52	170	40	10	80	1	30	10	5.477	0.570
53	210	70	10	80	1	60	32	4.055	0.528
54	210	40	50	40	5	60	32	3.623	0.516
55	170	40	50	40	1	30	10	5.477	0.570
56	210	70	50	80	1	60	10	7.206	0.707

Contd.

Table 3 — Design and result of central composite design experiments

No.	*A*	*B*	*C*	*D*	*E*	*F*	*G*	Volume shrinkage (%)	Warpage (mm)
57	210	40	50	40	1	30	32	4.045	0.526
58	210	40	50	40	5	30	10	6.527	0.616
59	170	40	50	80	1	30	32	3.003	0.454
60	170	40	10	40	5	30	10	4.907	0.514
61	210	70	10	80	1	30	10	7.189	0.704
62	210	40	50	80	1	30	10	7.189	0.704
63	210	40	10	40	5	30	32	3.613	0.514
64	210	70	50	40	1	30	10	7.189	0.704
65	190	55	30	60	3	45	32	3.151	0.455
66	210	40	10	40	5	60	10	6.546	0.618
67	190	55	50	60	3	45	21	4.383	0.485
68	170	40	10	40	5	60	32	2.852	0.444
69	170	70	50	80	5	30	32	2.809	0.436
70	170	70	50	40	1	30	32	3.002	0.454
71	170	70	10	40	5	30	32	2.809	0.436
72	170	55	30	60	3	45	21	3.829	0.474
73	210	40	50	40	1	60	10	7.206	0.707
74	170	40	50	40	1	60	32	3.021	0.457
75	210	40	10	80	5	30	10	6.527	0.616
76	210	70	50	40	5	30	32	3.612	0.514
77	190	55	30	60	3	30	21	4.373	0.483
78	170	40	50	40	5	30	32	2.809	0.436
79	190	55	30	60	3	45	21	4.383	0.485
80	170	40	50	80	5	60	32	2.852	0.444
81	210	40	10	40	1	60	32	4.055	0.528
82	170	40	10	80	1	60	32	3.021	0.457
83	170	70	10	40	1	60	32	3.021	0.457
84	190	55	30	60	3	45	10	5.940	0.574

Table 4 — NOVA table for volume shrinkage (after backward elimination)

Source	*df*	Adj SS	Adj MS	*F-Value*	*P-Value*
Model	9	152.124	16.903	28874.56	0
Linear	4	148.016	37.004	63213.4	0
A	1	27.411	27.411	46826.12	0
E	1	3.505	3.505	5987.89	0
F	1	0.009	0.009	15.47	0
G	1	117.091	117.091	200024.1	0
Square	2	1.388	0.694	1185.13	0
*A***A*	1	0.086	0.086	146.1	0
*G***G*	1	0.111	0.111	190.45	0
2-Way Interaction	3	2.72	0.907	1549.04	0
*A***E*	1	0.127	0.127	217.11	0
*A***G*	1	2.229	2.229	3807.85	0
*E***G*	1	0.364	0.364	622.18	0
Error	74	0.043	0.001		
Lack-of-Fit	69	0.043	0.001		
Pure Error	5	0	0		

Addition: S = 0.0241947, R-Sq = 99.97%, R-Sq(adjust) = 99.97%, R-Sq(prediction) = 99.96%

volume shrinkage. Analysis of variance (ANOVA) was selected to consider the significance of the model terms for warpage and volume shrinkage in Tables 4 and 5, respectively. The term “Seq SS” is the sum of squares for each term. It is used to validate of the data. “*df*” refers to degrees of freedom used to contribute to the error prediction. “Adj SS” is adjusted sum of squares that is used to be a sign after removing insignificant terms from the model. “Adj Ms” is adjusted mean squared for a term. Then both models are processed using the backward term elimination, which means some of the terms that are not significant

Table 5 – ANOVA table for warpage (after backward elimination)

Source	*df*	Adj SS	Adj MS	*F-Value*	*P-Value*
Model	9	0.4754	0.052822	1999.64	0
Linear	4	0.407981	0.101995	3861.13	0
A	1	0.146981	0.146981	5564.1	0
E	1	0.028821	0.028821	1091.05	0
F	1	0.000281	0.000281	10.62	0.002
G	1	0.231899	0.231899	8778.75	0
Square	2	0.045778	0.022889	866.48	0
*A**A*	1	0.003	0.003	113.56	0
*G**G*	1	0.003482	0.003482	131.83	0
2-Way Interaction	3	0.021641	0.007214	273.07	0
*A**E*	1	0.001027	0.001027	38.89	0
*A**G*	1	0.00756	0.00756	286.2	0
*E**G*	1	0.013053	0.013053	494.14	0
Error	74	0.001955	0.000026		
Lack-of-Fit	69	0.001955	0.000028		
Pure Error	5	0	0		

Addition: S = 0.0051396, R-Sq = 99.59%, R-Sq(adjust) = 99.54%, R-Sq(prediction) = 99.45%

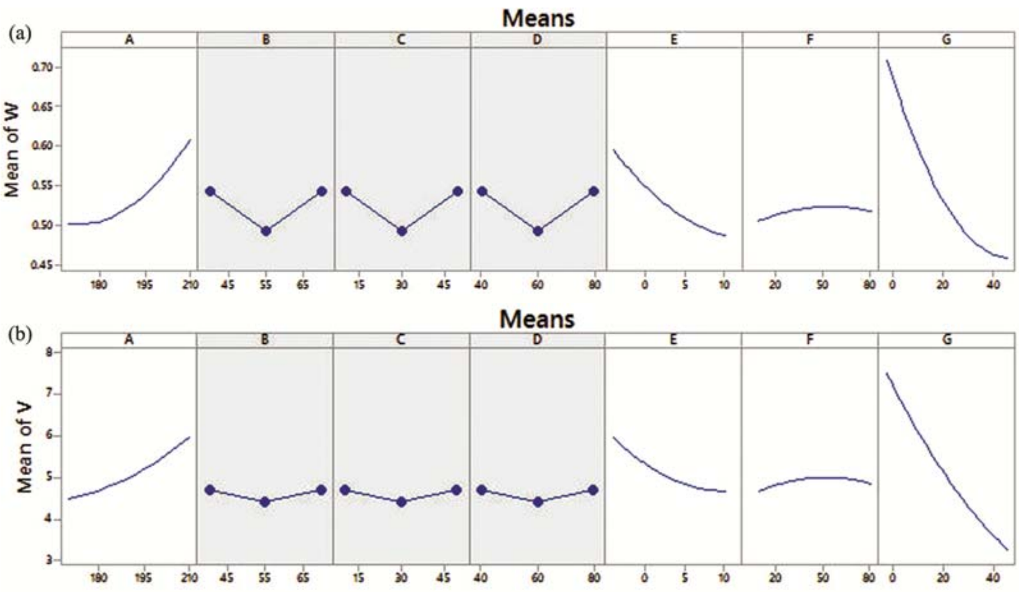

Fig. 6 — Main Effects Plots for warpage problem (a) and volume shrinkage problem (b) Addition: a gray background represents a term not in the model

are cut. Finally, Tables 4 and 5 show that "*P-value*" is less than 0.05 and the values of "R-Sq (prediction)" were more than 99% of both. Therefore, these tables of results found that melt temperature (*A*), mold temperature (*B*), maximum velocity injection (*C*), maximum injection pressure (*D*), packing time (*E*), maximum packing pressure (*F*), and cooling time (*G*), only four factors are significant, namely *A*, *E*, *F*, *G* as showing the main effect of warpage and volume shrinkage in Fig. 6. Thus, it can be concluded that these parameters have a tendency of effects that are the same for both problems as shown in Fig. 6, whereby if the melt temperature inclines continuously, the warpage and volume shrinkage will lead to minimized values and vice versa. Also packing pressure has a little tendency of effect, if it becomes low value; warpage and volume shrinkage will be minimized. Meanwhile packing time and cooling time are high, warpage and volume shrinkage will reduce continuously and vice versa. Moreover, Fig. 7(a) and (b) show interaction plots of three interaction factors that are significant with warpage and volume shrinkage, namely *A**E*, *A*G*, *E**G* after backward elimination of other interaction factors. They obviously are found that

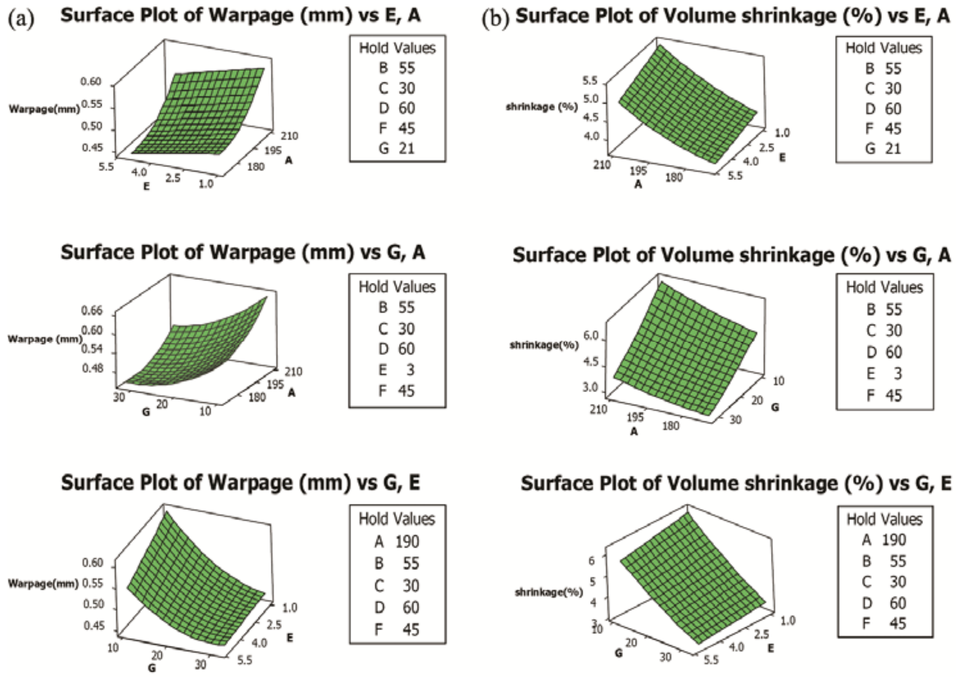

Fig. 7 — Interaction Plots for warpage problem after backward elimination (a) and volume shrinkage problem after backward elimination (b)

if the melt temperature inclines whereas packing time and cooling time climb high, both warpage and volume shrinkage will decrease continually. According to RSM method, it can simply generate the polynomial equation consisting of A, E, F, G, A^2, G^2, AE, AG, and EG terms. Thus, the final predicted models of warpage and volume shrinkage are given in Eqs (5) and (6), respectively.

$$\text{Warpage } (W) = 2.637 - 0.02329\,A - 0.00505\,E + 0.000137\,F - 0.00857\,G + 0.000071\,A*A + 0.000253\,G*G - 0.000100\,A*E - 0.000049\,A*G + 0.000649\,E*G \quad \ldots (5)$$

$$\text{Volume Shrinkage } (V) = 11.63 - 0.0907\,A + 0.0244\,E + 0.000781\,F - 0.03031\,G + 0.000379\,A*A + 0.001431\,G*G - 0.001114\,A*E - 0.000848\,A*G + 0.003429\,E*G \quad \ldots (6)$$

After created the predicted models, validation of the models was carried out by using experimental random tests of 18 test runs as shown in Table 6. The results were the average absolute percentage deviation of each model as 0.63 and 0.77, respectively.

Thus, these models that were used for GA and FA implementation to seek the minimization of warpage and shrinkage are reliable.

Optimization through GA and FA

Substituting Eqs (5) and (6) added into Eq. (4) to optimize processes of both GA and FA, respectively, all variable constraints were fed into an optimal structure. Figure 8 show experiments of wrench specimens. Table 6 compares the minimized values of warpage and shrinkage problems from recommendation condition (medium conditions), using GA and FA method. It can be seen that the result of recommendation condition provided the minimized values as 3.370% and 3.677% shrinkages and 0.460 mm and 0.494 mm warpages via Moldex 3D simulation and actual experiment respectively by providing 190°C melt temperature, 5 s packing time, 50% packing pressure, and 27.5 s cooling time. The GA result found that the minimized values were provided as 2.553% and 2.848% volume shrinkage and 0.426 mm and 0.447 mm warpage through Moldex 3D simulation and actual experiment respectively by using 175.44°C melt temperature, 3.17 s packing time, 20.22% packing pressure, and 44.91 s cooling time, and using the main control parameters as size of population at 100, crossing-over rate at 0.6, aberration rate at 0.2, and maximum generation at 600 iterations according to Guo *et al.*'s research[2].

Whereas FA result provided 2.377% and 2.556% shrinkage and 0.409 mm and 0.433 mm warpage through Moldex 3D simulation and actual experiment respectively by using 183.63°C melt temperature, 10 s packing time, 20% packing pressure, and 45s cooling time and using control conditions of the method as population size equal to 50, maximum number of iterations equal to 200, the maximum attractiveness at

Table 6 — Comparison of predicted *vs*. actual run based on Moldex 3D software

No.	*A* (°C)	*E* (s)	*F* (%)	*G* (s)	Volume shrinkage (%)	Warpage (mm)	Predicted volume shrinkage (%)	Predicted warpage (mm)	% volume shrinkage deviation	% warpage deviation
1	170	1	30	10	5.475	0.577	5.455	0.574	-0.36%	-0.43%
2	170	2	37.5	13.75	4.872	0.522	4.829	0.524	-0.89%	0.38%
3	170	3	45	17.5	4.243	0.486	4.269	0.485	0.62%	-0.11%
4	190	4	30	10	5.766	0.560	5.719	0.555	-0.82%	-0.86%
5	210	3	37.5	21.25	5.186	0.550	5.134	0.559	-1.01%	1.59%
6	210	4	45	25	4.545	0.534	4.521	0.531	-0.52%	-0.55%
7	210	5	52.5	10	6.513	0.612	6.521	0.623	0.12%	1.77%
8	170	1	60	21.25	4.076	0.488	4.058	0.485	-0.46%	-0.61%
9	170	2	30	25	3.502	0.466	3.562	0.458	1.66%	-1.71%
10	170	3	37.5	10	5.198	0.542	5.199	0.544	0.03%	0.46%
11	180	3	45	13.75	5.064	0.521	4.987	0.518	-1.55%	-0.58%
12	190	1	37.5	25	4.136	0.480	4.115	0.483	-0.52%	0.81%
13	190	4	60	17.5	4.727	0.496	4.705	0.497	-0.48%	0.18%
14	200	2	52.5	25	4.377	0.502	4.362	0.507	-0.34%	0.96%
15	200	3	60	10	6.377	0.613	6.348	0.613	-0.45%	0.08%
16	210	3	30	21.25	5.176	0.548	5.128	0.558	-0.92%	1.70%
17	210	4	37.5	25	4.532	0.532	4.516	0.530	-0.37%	-0.43%
18	210	5	45	10	6.528	0.618	6.515	0.622	-0.20%	0.64%

% deviation was calculated using the equation: [(predicted value – simulated value)/predicted value] x100

Table 7 — Volume shrinkage and warpage values before and after optimization methods

Objectives	Recommended condition method		GA method		FA method	
	Moldex 3D simulation	Experiments	Moldex 3D simulation	Experiments	Moldex 3D simulation	Experiments
Volume shrinkage (%)	3.370	3.677	2.553	2.848	2.553	2.556
Warpage (mm)	0.460	0.494	0.426	0.447	0.426	0.433

0.5, the absorption coefficient at 0.5, and the random perturbation rate at 0.2 according to Lobato and Steffen's research[18]. For the comparison of actual experiments and Moldex 3D simulated tests found that empirical results provide experimental values nearby simulated values at 94% and 90% accuracy of warepage and volume shrinkage respectively.

Comparison of RSM, GA and FA results

The results from both optimization methods clearly show that the FA performance can generate better results than GA and at recommended condition performances as shown in Table 7. Warpage and volume shrinkage that are provided from FA algorithm achieve better minimized values than GA algorithm at 4.05% and 7.4% respectively, and better than the recommended condition 11.33% and 41.73% for warpage and volume shrinkage by Moldex 3D simulated tests. Similarly, FA algorithm provides better minimized values than GA algorithm at 3.28% and

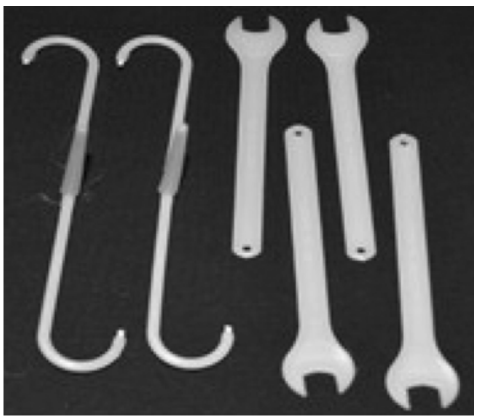

Fig. 8 — wrench example part from actual experiments

10.26% respectively, and better than the recommended condition 12.42% and 30.49% for warpage and volume shrinkage by experiments through Toshiba 80T injection molding machine. Meanwhile GA performance can provide minimized values of warpage and volume shrinkage better than at recommended condition at 9.45% and 22.54% respectively. Therefore, this research experiment can conclude that use of FA algorithm can find suitable process parameters to minimize warpage and volume shrinkage better than GA implementation according to Yang's research[15,16] that proved FA algorithm performance better than the performance of the popular GA algorithm.

Conclusions

This research deals with the study of the minimization of warpage and volume shrinkage problems. An optimization model using FA was successfully compared with GA by both algorithms developed and based on the second-order response surface regression methodology. This research seeks to provide a flexible and better optimization model to discover suitable process parameters to accommodate moveable limitations, conditions, and constraints of different injection molding machines. For this study, general purpose polystyrene was employed for analysis; it was found that melt temperature and cooling time were the main influences for warpage and volume shrinkage. Packing time and packing pressure were the next priorities. This conclusion can be applied to consider process parameters to reduce warpage and volume shrinkage for global allowable ranges for the injection molding process. Moreover, this research illustrates that the Firefly algorithm for optimizing process parameters is another one that can produce better results of warpage and volume shrinkage reduction than the previously favored genetic algorithm, which has been widely employed in plastic injection molding processes.

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References

1 Chaiang K T & Chang F P, *Int J Adv Manuf Technol*, 35 (2006) 468-479.
2 Guo W, Hua L & Mao H, *Int J Adv Manuf Technol*, 72 (2014) 365-375.
3 Zhao J, Cheng G, Ruan S & Li Z, *Int J Adv Manuf Technol*, 78 (2015) 1813-1826.
4 Santos J D, Fajardo J I, Cuji A R, Carcía J A, Garzón L E & López L M, *Front Mech Eng*, 10 (2015) 287-293.
5 Chiang Y C, Cheng H C, C F, Lee J L, Lin Y & Shen Y K, *Int J Adv Manuf Technol*, 55 (2010) 517-526.
6 Kashyap S & Datta D, *Int J Plast Technol*, 19 (2015) 1-18.
7 Zheng G, Guo W, Wang Q & Guo X, *J Mech Sci Technol*, 29 (2015) 4153-4158.
8 Erzurumlu T & Ozcelik B, *Mater Des*, 27 (2006) 853-861.
9 Lam Y C, Britton G A & Deng Y M, *Int J Adv Manuf Technol*, 22 (2013) 574-586.
10 Lin J & Lian R J, *J Process Control,* 20 (2010) 585-595.
11 Shi H, Suming S & Wang X, *Int J Adv Manuf Technol*, 65 (2012) 343-353.
12 Xu G, Yang Z T & Long G d, *Int J Adv Manuf Technol*, 58 (2011) 521-531.
13 Ozcelik B & Erzurumlu T, *J Mater Process Technol*, 171 (2005) 437-445.
14 Beng Y M, Zhang Y & Lam Y C, *Mater Des*, 31 (2009) 2118-2123.
15 Yang X S, *J Eng Comput*, 29 (2013) 175-184.
16 Yang X S, *Am J Appl Math Stat*, 5792 (2009) 169-178.
17 Chen C C, Su P L & Lin Y C, *Int J Adv Manuf Technol*, 45 (2009) 1087-1095.
18 Lobato F S & Steffen J V, *Am J Appl Math Stat*, 1 (2013) 110-116.