Springer

KSME

Journal of Mechanical Science and Technology 26 (4) (2012) 1133~1139
www.springerlink.com/content/1738-494x
DOI 10.1007/s12206-012-0214-0

Prediction of warpage in plastic injection molding based on design of experiments †

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(Manuscript Received May 27, 2011; Revised November 3, 2011; Accepted November 3, 2011)

Abstract

In terms of injection processing parameters, a mathematical model for prediction of warpage was formulated based on design of experiments (DOE). First, the five most influential parameters were screened by using fractional factorial design (FFD): melt temperature, coolant temperature, injection time, V/P switch over and mold temperature. Second, considering the other four principal processing parameters except the melt temperature, the predicting mathematical model was founded by using central composite design (CCD) of experiments and FE simulation. Finally, the results of statistical analysis were collected from software Moldflow. The results suggested that the mathematical model can be used to predict warpage with adequate accuracy. Hence, it indicated that corrective and iterative design steps can be initiated and implemented for better quality of products without resorting to physical trials in plastics injection mold by using this predicting mathematical model.

Keywords: Warpage; DOE; FFD; CCD; Plastics injection molding

1. Introduction

Plastics injection molding is nothing but one of the major net-shape-forming processes for thermoplastics materials. There are several defects that occur in the injection molding process, including warpage, sink mark, air traps and weld lines, etc. Warpage, which is a part defect caused by a non-uniform change of internal stresses, is considered to be one of the most difficult to control. However, it can be controlled by the optimization of process parameter setting. The parameter settings were considered to be a “black art,” which relies heavily on the experience and knowledge of experts and involves a great deal of trial-and-error [1].

In the last decade, many researches are trying to eliminate the costly trial-and-error process. Huang et al. [2] pointed out that the most influential parameter on warpage was packing pressure, and the warpage was only slightly influenced by the gate dimension and the filling time in thin shell injection molding; they also discussed the optimum values of the processing parameters to decrease the warpage. Ozcelik et al. [3] also found that packing pressure was the most influential parameter on the warpage of PC/ABS material by using Taguchi experimental method and CAE software Moldflow Plastic Insight 4.0. The warpage analysis was performed in terms of melt temperature, mold temperature, packing pressure and packing time. Kong et al. [4] studied the effect of several important parameters, including processing parameters, package geometry and materials on the warpage. Results indicated that the warpage can be reduced significantly with a lower molding temperature and a smaller coefficient of thermal expansion. Kurtaran et al. [5] chose a bus ceiling lamp base as the research model. The optimum values of processing parameters to reach minimum warpage were found by using the neural network model and genetic algorithm. Gao et al. [6] developed an effective optimization method by using the Kriging model to minimize the warpage in PIM.

The experimental method has been widely used by many researchers for optimization of injection molding process to control defects. Wang et al. [7] in their study used Taguchi experimental design to optimize the processing parameters during injection molding to minimize the warpage of the front panel of a large LCD TV. Patel and Mallick [8] used first-order response surface methodology (RSM)-based on DOE to reduce defects (the sink index was chosen as optimum response) in plastics injection molding. Wu-Lin Chen et al. [9] found the optimal values of process parameters in injection molding to minimize both warpage and shrinkage. The experimental results were collected by using the finite element software Moldflow. Dual response surface method with nonlinear programming was used to get the optimal values, which was then proved by re-running experiments on Moldflow. Ozcelik [3] et al., used the Taguchi method for research.

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Mathivanan and Parthasarathy [10, 11] designed a simple generic model to investigate the effects of parameters on the defect (sink mark depth). In their studies, the most influential parameter was screened and a nonlinear mathematical model was established to predict the sink mark depth.

In this study, an automotive interior trim was selected as the research model. At first, a factorial design of experiments was set up to determine the effects of the process parameters on warpage, which included mold temperature, melt temperature, coolant temperature, injection time, V/P switch over, packing time, packing pressure and coolant Reynolds number. After the FFD experiments, a mathematical model was established to predict warpage; that was based on central composite design of experiments. Finally, a statistical analysis was conducted in software Moldflow, and the results were compared with the prediction results.

2. Experimental setup

To conduct the experiments successfully, the research geometrical model, a suitable grade of thermoplastics material and a mold are required. Meanwhile, the FE model for flow simulation is also a requisite. The following sections describe these in detail.

2.1 Plastic part model and thermoplastic material.

For the design of experiments, the automotive interior trim was selected as the research model, which was designed in UG. The trim was assembled on the sheet-metal part, so high dimensional stability was needed. The trim is shown in Fig. 1. The part's dimensions were 260 mm × 450 mm × 70 mm, and the part base wall was fixed at 2 mm. In this study, Kingfa Sci & Tech Co Ltd, PP copolymer from Moldflow Plastics was selected. Its properties are given in Table 1.

Table 1. Properties of material.

PVT properties		Mechanical properties	
Solid density (g/cm^3)	0.89163	Elastic modulus (MPa)	1340
Melt density (g/cm^3)	0.72828	Shear modulus (MPa)	481
Recommended mold Temperature (℃)	30	Poisson's ratio	0.392
Recommended melt Temperature (℃)	220		
Ejection temperature (℃)	101		
Material characteristics	PP		

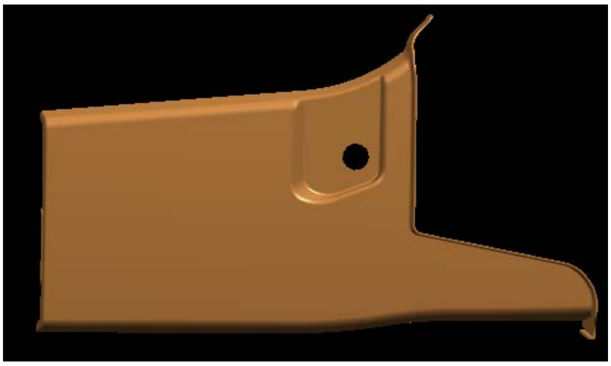


Fig. 1. The automobile housing trim.

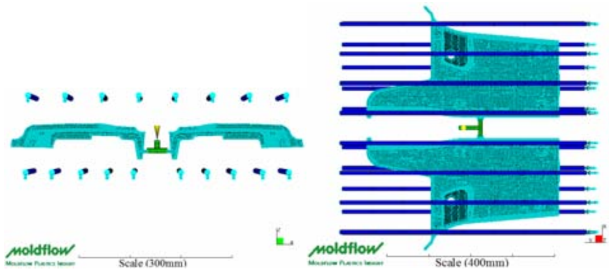


Fig. 2. The view of FE model of trim and mold.

2.2 Mold and molding machine

A proper mold is essential to mold a component in plastics injection molding. Mold design mainly contains a runner system, which is to feed the hot melt materials into the cold mold; and a cooling system to solidify the hot melt and an ejection system to eject the product from the mold. Here, the runner system was designed to have uniform flow based on standard mold design guidelines, which is shown in Fig. 2. Eighteen cooling channels with ten-millimeter-diameter were designed to maintain the required mold temperature.

2.3 FE model of the trim and mold for simulation

Mathematical model was adopted as an analytical model for FE simulation. The 3D part model was designed by using UG. FE model of this trim was created by meshing into smaller simple triangular elements in Moldflow software. The FE model of the trim contains 15195 triangular elements, the mesh type was midplane, and mesh was thoroughly checked to eliminate mesh-related errors. According to the mold design, the FE models of the runner system and cooling system were also created by using Moldflow, as shown in Fig. 2.

3. Experimental setup

Plastics injection molding can be treated like a system that contains a set of input and output. The aim of this paper is to establish the relationships of the input to output. There are many variables that affect the plastics injection molding process (Fig. 3).

3.1 Fractional factorial designs of experiments

If any experiment involves the study of the effects of two or more factors, then factorial designs are more efficient than one-factor-at-a-time experiments. Furthermore, a factorial design is necessary when interactions may be present to avoid misleading conclusions [12]. Hence, the proposal of FFD is suitable to arrive at the most influential processing parameters

Table 2. The process parameters and their levels.

Number	Process parameters	Levels	
		Low	High
1	Mold temperature (℃)	20	40
2	Melt temperature (℃)	200	240
3	Injection time (s)	1.8	2.2
4	V/P switch-over	97%	99%
5	Packing pressure (% Inject P)	60	100
6	Packing time (s)	26	30
7	Coolant temperature (℃)	20	40
8	Coolant Reynolds number	8000	12000

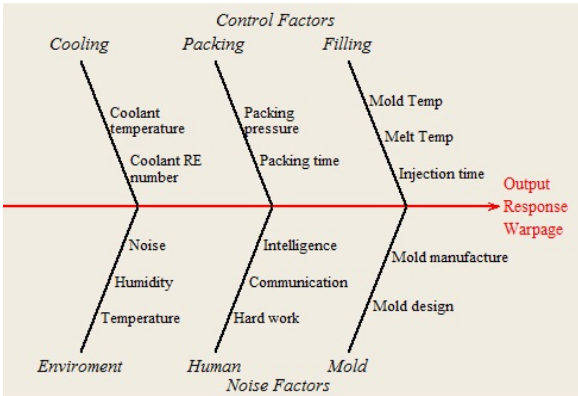


Fig. 3. System of plastics injection molding.

and their effects. In this section, L16 FFD array was used to find the effects of the processing parameters on warpage. The processing parameters and their levels are indicated in Table 2. Factors like runners, cooling system, desirable ejection temperature and mold material were generally fixed. The reasons for this were as follows: (1) The foundation of runners and cooling system was based on the design of mold designer, whose correctness has been demonstrated; (2) Ejection temperature, which depends on cooling time, guarantees proper solidification of melt and assures structural rigidity as required by the design intent of the product. Cooling time, in turn, was dependent on other processing parameters like melt temperature, coolant temperature, coolant flow rate. Hence, arbitrarily setting up of ejection temperature limits is not advisable [11]. In this study, the ejection temperature was set at as 101℃.

3.2 Central composite design of experiments

CCD is nothing but 2^k factorial design augmented with center points and axial points. CCD is far more efficient than running 3^k factorial design with quantitative factors [14]. To optimize processing parameters, central composite design (CCD) is one of the most important experimental designs. We employed the CCD method to develop the mathematical model to predict warpage. According to the results of FFD experiments, four processing parameters out of the eight variables were chosen for CCD experiments. The four processing parameters and levels are shown in Table 3.

Table 3. Processing parameters and their levels for CCD.

Code level	A $T_{cooling}$ (℃)	B $t_{injection}$ (s)	C V/P	D T_{mold} (℃)
-1	20	1.8	97%	20
-1/2	25	1.9	97.5%	25
0	30	2.0	98%	30
1/2	35	2.1	98.5%	35
1	40	2.2	99%	40

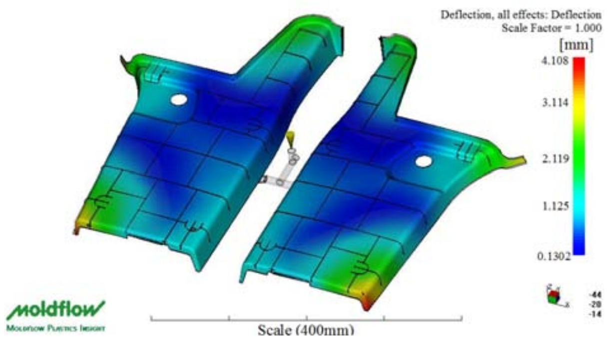


Fig. 4. Warpage results of CAE from Moldflow.

To develop the mathematical model, a polynomial equation was established to show the influences of the processing parameters on the warpage (Eq. (1)). In this section, the software Minitab was used to analyze and obtain different coefficients of the polynomial equation.

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

where W means the value of the warpage, B_0, B_i and B_{ij} are coefficients which will be achieved from software Minitab, X_i and X_j stand for the level of different factors.

4. Results and analysis

This section discusses the results of FFD and CCD experiments and the mathematical prediction model developing. The warpage result of CAE from software Moldflow is shown in Fig. 4. In light of the analysis results, the highest value of warpage was displayed as red.

4.1 Analysis of FFD experiments

A total of 16 trials were conducted and the maximum warpage values were measured in software Moldflow. Recorded warpage values along with FFD array are tabulated in Table 4. The magnitude and the importance of the influence of processing parameters was plotted in a Pareto chart (Fig. 5). It

Table 4. L_{16} FFD array and warpage results.

NO	T_{mold} (℃)	T_{melt} (℃)	t_{inject} (s)	V/P	P_{pack}	t_{pack}	T_{cool} (℃)	RE number	Warpage (mm)
1	20	200	1.8	99%	100%	30	20	120000	4.687
2	20	240	2.2	97%	60%	30	20	120000	4.370
3	20	240	1.8	97%	100%	26	40	120000	4.093
4	40	240	2.2	97%	60%	26	40	80000	4.025
5	40	240	1.8	99%	60%	26	20	120000	4.229
6	20	240	1.8	99%	60%	30	40	80000	4.081
7	40	200	1.8	99%	100%	26	40	80000	4.451
8	40	200	2.2	97%	100%	26	20	120000	4.510
9	20	200	1.8	97%	60%	26	20	80000	4.444
10	20	240	2.2	99%	100%	26	20	80000	4.047
11	20	200	2.2	97%	100%	30	40	80000	4.435
12	40	200	1.8	97%	60%	30	40	120000	4.398
13	40	240	2.2	99%	100%	30	40	120000	3.577
14	40	200	2.2	99%	60%	30	20	80000	4.277
15	40	240	1.8	97%	100%	30	20	80000	4.225
16	20	200	2.2	99%	60%	26	40	120000	4.257

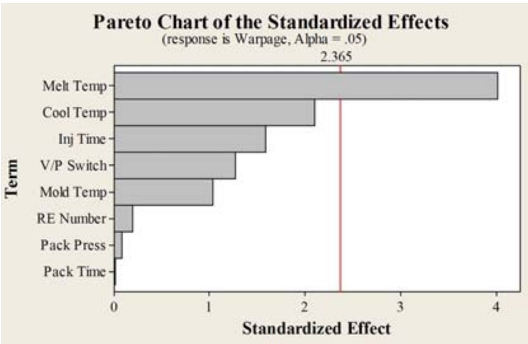


Fig. 5. Pareto chart of FFD experiments.

indicated that the absolute value of melt temperature extended past the reference line, while the other values of parameters were much smaller when compared with melt temperature. Thus, the melt temperature was the key parameter to influence the warpage. It can also be indicated that other significant processing parameters were cooling temperature, injection time, V/P switch over and mold temperature in order.

Range analysis was also used to find the principal factor that affected the warpage. The results of range analysis are shown in Fig. 6. The value of R in Fig. 6 was indicated as Eqs. (2) and (3), where Wij is the value of warpage of factor i and level j. Ki is the average value of the sum of Wij. The value Ri is the difference between maximum and minimum of the factor i. The larger absolute value R is, the greater the influence of the factor to warpage is. According to Fig. 6, it can also be confirmed that melt temperature made the most significant contribution to influence warpage form Fig. 6.

$$K_i = \frac{1}{8}\sum_{j=1}^{8} W_{ij}, \tag{2}$$

$$R_i = K_{low} - K_{high}. \tag{3}$$

Table 5. Results of CCD experiments.

No	T_{cool} (℃)	t_{inject} (s)	V/P	T_{mold} (℃)	Warpage (mm)	Predicted warpage (mm)	Residual error (mm)
1	-1	1	1	-1	4.108	4.10429	0.00371
2	1	-1	1	1	4.084	4.08908	-0.00508
3	1	1	1	-1	3.764	3.78825	-0.02425
4	-1	-1	-1	-1	4.253	4.24713	0.00587
5	1	-1	-1	-1	4.084	4.10258	-0.01858
6	1	-1	1	-1	4.084	4.09796	-0.01396
7	-1	1	-1	1	4.071	4.06729	0.00371
8	0	0	0	0	4.097	4.09888	-0.00188
9	1	-1	-1	1	4.082	4.09596	-0.01396
10	0	0	0	0	4.097	4.09888	-0.00188
11	-1	-1	-1	1	4.253	4.24475	0.00825
12	-1	-1	1	1	4.182	4.22113	-0.03913
13	-1	1	1	1	4.098	4.09542	0.00258
14	-1	-1	1	-1	4.175	4.22575	-0.05075
15	1	1	-1	-1	3.770	3.74113	0.02887
16	1	1	1	1	3.759	3.77513	-0.01613
17	1	1	-1	1	3.765	3.73025	0.03475
18	0	0	0	0	4.097	4.09888	-0.00188
19	0	0	0	0	4.097	4.09888	-0.00188
20	-1	1	-1	-1	4.063	4.07392	-0.01092
21	0	0	0	0	4.097	4.09888	-0.00188
22	0	0	2	0	4.094	4.04125	0.05275
23	0	0	0	2	4.054	4.06025	-0.00625
24	0	0	0	0	4.097	4.09888	-0.00188
25	0	2	0	0	3.805	3.83492	-0.02992
26	-2	0	0	0	4.251	4.23142	0.01958
27	0	0	-2	0	3.980	4.01775	-0.03775
28	2	0	0	0	3.762	3.76658	-0.00458
29	0	0	0	-2	4.097	4.07575	0.02125
30	0	-2	0	0	4.367	4.32208	0.00371

Residual error = Predicted Warpage – Warpage of CAE

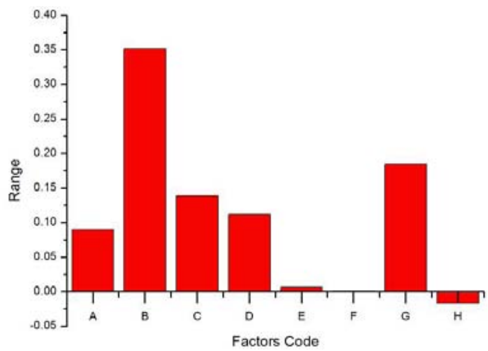


Fig. 6. Results of range analysis.

4.2 Analysis of CCD experiments

According to the results of FFD experiments, the melt temperature was constant at the middle level to investigate the influences of the other four significant processing parameters by using CCD. The processing parameters and their levels are listed in Table 3. A total number of 30 trials were conducted and the maximum warpage values were collected from software Moldflow. Table 5 shows the levels of the factors and results of the CCD experiments.

Table 6. Estimated regression coefficients for warpage.

Term	Coef	SE Coef	T	P
Constant	4.09700	0.013310	307.820	0.000
A	-0.11621	0.006655	-17.462	0.000
B	-0.12179	0.006655	-18.301	0.000
C	0.00587	0.006655	0.883	0.391
D	-0.00387	0.006655	-0.582	0.569
A×A	-0.02497	0.006225	-4.011	0.001
B×B	-0.00509	0.006225	-0.818	0.426
C×C	-0.01734	0.006225	-2.786	0.014
D×D	-0.00772	0.006225	-1.240	0.234
A×B	-0.04706	0.008151	-5.774	0.000
A×C	0.00419	0.008151	0.514	0.615
A×D	-0.00106	0.008151	-0.130	0.898
B×C	0.01294	0.008151	1.587	0.133
B×D	-0.00106	0.008151	-0.130	0.898
C×D	-0.00056	0.008151	-0.069	0.946

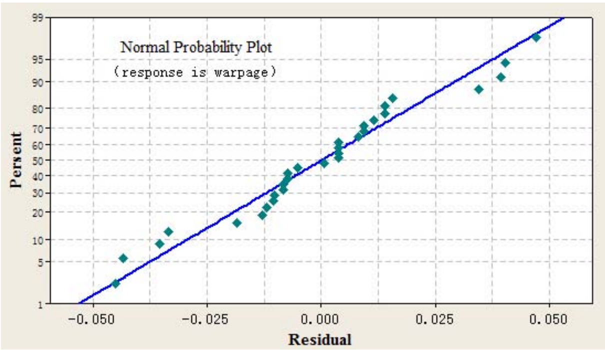


Fig. 7. Normal probability plot for residuals.

Minitab was used to analyze the CCD experiments. The estimated coefficients for the warpage predication are shown in Table 6. The term "coef" means coefficients, standing for relationships between warpage and the processing parameters. The values of term "SE coef" were calculated to stand for the error of setting up coefficients, and the smaller values of "SE coef" lead to a better precision of coefficient. The term T is the ratio of "coef" and "SE coef" which could be used to examine whether the predictor significantly predicts the response warpage. The P value can be used to test whether the effect of processing parameters was significant. In this section, A, B, A^2, AB and C^2 were significant model terms to the response warpage. In light of Table 5, the response equation for warpage can be coded as Eq. (4). According to Eq. (4), the predicative values of warpage for the 30 experiments are also tabulated in Table 6. Fig. 7 shows the residual plot. The mathematical predication model was quite reliable for the data and was well imitated as shown in Fig. 7.

$$\begin{aligned} Warpage = {} & 4.09888-(1.1621\times10^{-1})A-(1.2179\times10^{-1})B+(5.87\times10^{-3})C \\ & -(3.87\times10^{-3})D-(2.497\times10^{-2})A^2-(5.09\times10^{-3})B^2-(1.734\times10^{-2})C^2 \\ & -(7.72\times10^{-3})D^2-(4.706\times10^{-2})AB+(4.19\times10^{-3})AC-(1.06\times10^{-3})AD \\ & +(1.294\times10^{-2})BC-(1.06\times10^{-3})BD-(5.6\times10^{-4})CD \end{aligned} \tag{4}$$

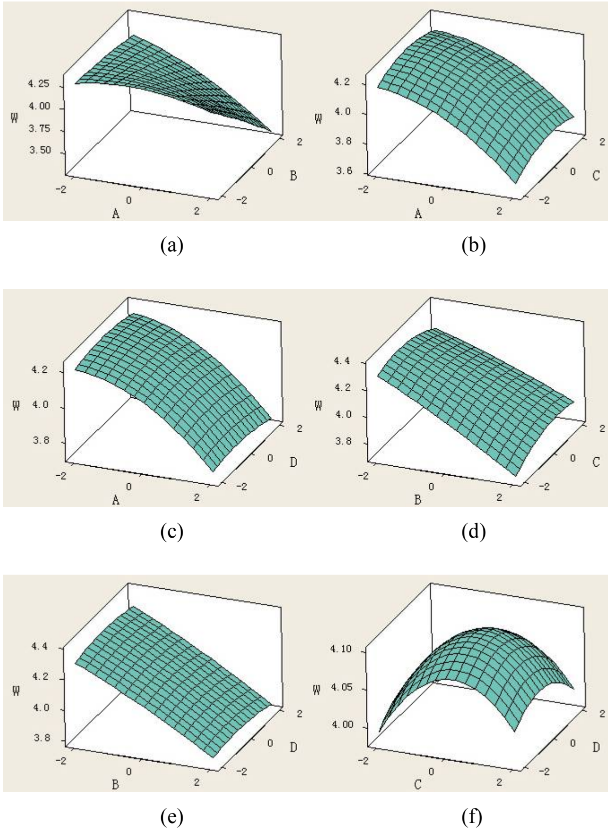


Fig. 8. 3D Surface plots for the response—warpage: (a) cooling temperature vs injection time; (b) cooling temperature vs V/P switch over; (c) cooling temperature vs mold temperature; (d) injection time vs V/P switch over; (e) injection time vs mold temperature; (f) V/P switch over vs mold temperature.

The surface plots for the response—warpage are shown in Fig. 8. As shown in Fig. 8, the following observations can be made: (1) From the 3D surface plots in Fig. 8(a)-(c), increased cooling temperature had a positive influence on warpage reduction. (2) In light of Fig. 8(a), (c), (e), short injection time, in general, led to less warpage. It was also observed that, with the increase of the injection time, the value of the warpage was reduced more significantly when the cooling temperature was at high level than that was at low level. (3) The value of the warpage would increase first and decrease subsequently while increasing the value of V/P switch-over. Meanwhile, decreasing the value of V/P switch-over in combination with increased cooling temperature and injection time caused a rapid reduction in warpage. (4) Mold temperature variation had minor influence on the warpage.

5. Confirmation test

A total of 25 experiments were conducted to test the mathematic model. Table 7 shows the processing parameter settings, predicted responses for warpage, results of CAE, and percentage residual error for each running. The warpage results of CAE were measured from the software Moldflow.

Table 7. Comparison of CAE vs predicted.

No	T_{cool}(℃) /level	t_{inject}(s) /level	V/P /level	T_{mold}(℃) /level	Warpage (mm)	Predicted warpage (mm)	Residual error (mm)
1	25/-0.5	2.1/0.5	98.5%/0.5	25/-0.5	4.102	4.1012725	0.0007275
2	35/0.5	1.9/-0.5	98.5%/0.5	35/0.5	4.101	4.0983275	0.0026725
3	35/0.5	2.1/0.5	98.5%/0.5	25/-0.5	3.959	3.9641575	-0.0051575
4	25/-0.5	1.9/-0.5	97.5%/-0.5	25/-0.5	4.198	4.1949475	0.0030525
5	35/0.5	1.9/-0.5	97.5%/-0.5	25/-0.5	4.103	4.1007025	0.0022975
6	35/0.5	1.9/-0.5	97.5%/0.5	25/-0.5	4.115	4.1024775	0.0125225
7	25/-0.5	1.9/0.5	97.5%/-0.5	35/0.5	4.098	4.0871575	0.0108425
8	30/0	2.0/0	98%/0	30/0	4.097	4.09888	-0.00188
9	35/0.5	1.9/-0.5	97.5%-0.5	35/0.5	4.091	4.0971125	-0.0061125
10	25/-0.5	1.9/-0.5	97.5%/-0.5	35/0.5	4.185	4.1924175	-0.0074175
11	25/-0.5	1.9/-0.5	98.5%/0.5	35/0.5	4.199	4.1894425	0.0095575
12	25/-0.5	2.1/0.5	98.5%/0.5	35/0.5	4.088	4.0971225	-0.0091225
13	25/-0.5	1.9/-0.5	98.5%/0.5	25/-0.5	4.189	4.1925325	-0.0035325
14	35/0.5	2.1/0.5	97.5%/-0.5	25/-0.5	3.929	3.9494425	-0.0204425
15	35/0.5	2.1/0.5	98.5%/0.5	35/0.5	3.961	3.9589475	0.0020525
16	35/0.5	2.1/0.5	97.5%/-0.5	35/0.5	3.952	3.9447925	0.0072075
17	25/-0.5	2.1/0.5	97.5%/-0.5	25/-0.5	4.079	4.0907475	-0.0117475
18	30/0	2.0/0	99%/2	30/0	4.077	4.04126	0.03574
19	30/0	2.0/0	98%/0	40/2	4.059	4.06026	-0.00126
20	30/0	2.2/2	98%/0	30/0	3.841	3.83494	0.00606
21	20/-2	2.0/0	98%/0	30/0	4.229	4.23142	-0.00242
22	30/0	2.0/0	97%/-2	30/0	4.021	4.01778	0.00322
23	40/2	2.0/0	98%/0	30/0	3.776	3.76658	0.00942
24	30/0	2.0/0	98%/0	20/-2	4.083	4.07574	0.00726
25	30/0	1.8/-2	98%/0	30/0	4.311	4.3221	-0.0111

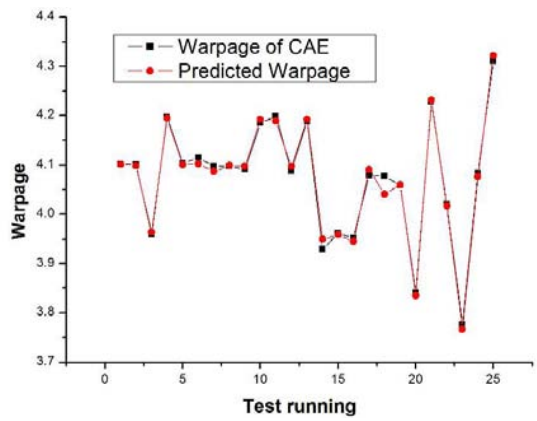
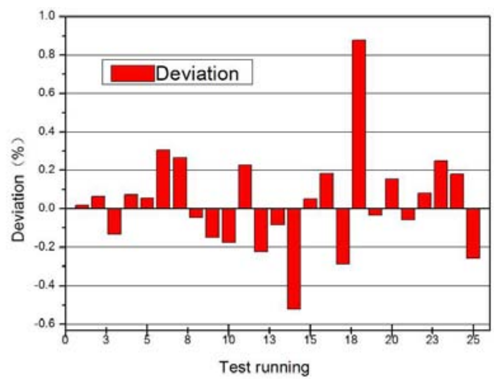


Fig. 9. Predicated warpage vs warpage of CAE.



Deviation = [(Predicted Warpage – Warpage of CAE)/Warpage] × 100

Fig. 10. Percentage deviation of test experiments.

The predicted warpage values were figured out according to Eq. (4). The graphical presentation of predicted versus CAE results of the 25 tests running is shown in Fig. 8. The percentage deviations of test experiments are shown in Fig. 9. In light of Table 7, Figs. 9 and 10, it could be found that the maximal residual error was 0.03574mm, and the percentage deviation varied between -0.5203% and 0.8766%. Hence, the accuracy of the mathematical predicated model was reliable, which was established based on DOE.

6. Conclusion

A mathematical model was successfully developed to predict the response (warpage) based on DOE and CAE simulation. The accuracy and agreement of the model were tested by the confirmation experiments. According to the test experiments, deviations were found to be within -0.5203% and 0.8766%. In light of central composite design (CCD), the interactions between the principal processing parameters were studied and discussed in detail in Part 4.2.

Not only can this methodology be used for warpage defects, but also extended to other defects such as sink mark depth, shrinkages and so on. Moreover, this methodology can be deployed for new product design and any continuous product improvement.

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