A Statistical Experimental Study on Shrinkage of Injection-Molded Part

S.Rajalingam[1], Awang Bono[2] and Jumat bin Sulaiman[3]

Abstract— Plastic injection molding is an important process to produce plastic parts. However, the difficulty in determining optimum process parameters setting may cause defects of the injected molded parts such as shrinkage. In this study the authors investigate the process parameters which will affect the shrinkage defect on a plastic cell phone shell component. The process parameters selected in this study are the mould temperature, injection pressure and screw rotation speed. The Design of Experimental (DOE) approach was used to investigate and identify the optimal moulding process parameters setting. The significant factors affecting the length and width of the cell phone shell were identified from ANOVA. Statistical results and analysis are used to provide better interpretation of the experiment. Confirmation run with the optimal process parameter setting found by DOE method determined that the shrinkage defect can be eliminate during mass production.

Keywords- Injection moulding, factors, responses, target value and model.

I. Introduction

IN recent years, the communication products like cell phone are widely applied throughout the world. The designs of cell phone have to be thin, light and small and more convenient style. Therefore, the shapes of cell phone are changing, and more features have to be tightly packed into smaller volumes within the shell. Injection molding is the most commonly used manufacturing process for the fabrication of plastic products [1].

One of the most common defects in injection molding industry is ‘shrinkage’ which influence the dimensional accuracy of molded product. There are several researchers that have studied the effects of injection molding process parameters on the shrinkage defect [2,3,4,5]. Many factors such as polymer materials, product design and process parameters can affect the shrinkage behavior.

Optimal process parameter setting is consider as one of the most important steps in injection molding for improving the quality of molded products [6]. However, the optimal process parameters setting for the molding operation becomes more difficult as the wall thickness of plastic products gets thinner. Previously, production engineers used either trial-and-error method or one-factor-at-time (OFAT) method to determine the molding optimal process parameter settings.

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In research by Hsu [7], he argued that with a trial-and-error method, it is impossible to determine the actual optimal parameter settings. In OFAT’s method, optimization is usually carried out by varying a single factor while keeping all other factors fixed in a specific set of conditions [8]. The major disadvantage of the OFAT method is that it fails to consider any possible interaction between the factors. Although some individuals think that OFAT is a scientific method [9] but OFAT method usually incapable of reaching the true optimum due to ignoring the interactions among variables [10]. Therefore, both methods (trial-and error and OFAT) are unsuitable in present injection molding industry because the increasing complexity of product designs and the requirement of multi-response quality characteristics like shrinkage.

Experimentation is made to determine the effect of the independent variables (factors) on the dependent variables (responses) of a process and a relation between them illustrated by a regression model by using experimental data. Statistical design of experiment (DOE) is a well known efficient experimentation technique and has been applied in a wide range of fields such as drug and food industry, chemical and biological, manufacturing processes, etc., to produce high quality products, to operate more economical process, to ensure more stable and reliable process [11].

In this paper the authors used Design of Experiment (DOE) method in a case study to investigate the injection moulding process parameters which will affect the dimensions of a plastic cell phone shell (hereafter referred to as the plastic front cover) due to shrinkage. Therefore the experiment is needed to identify the optimal molding process parameters which could be maintain the dimensions closest to the target value with smallest possible variation.

II. Experimental set-up

The material used to manufacture the front cover was commercially available polycarbonate (PC) material. In this experiment three factors are being studied and their levels are given in table I. The average value of a factor is equal to center point. The three factors are mould temperature, injection pressure and screw rotation speed and it is labeled as A, B and C respectively. The levels of the factors determined according to our experience about the process and from the literature research.

The mold is with two measurable responses are the length and width of the front cover. The injection molding process setting in use currently caused variations in the dimensions below the specification limit of length and width of front cover. The specification limit for the length and width are 93.49 ± 0.2 mm and 45.93 ± 0.2 mm respectively. The objective of this experiment is to identify the optimal molding process parameter setting which could be set to maintain both dimensions closest to the target values with smallest possible variation. The target values for length and width are 93.49 mm and 45.93 mm respectively.

Table I: Experimental control factors and its levels.

Symbol	Factors	Units	Low Level (-)	High Level (+)	Center Point (0)
A	Mould Temperature	°C	85	95	90
B	Injection Pressure	kg/cm^2	2250	2400	2325
C	Screw Rotation Speed	mm/Sec	110	140	125

A full two level factorial experimental design with center point was carried out to study on how the above three factors will influence the responses. The number of run needed according to full two-level factorial experimental design method for three factors was eight and the run was repeated twice and the authors like to add another two centre points to provide sufficient information on possible curvature in the system. Therefore a total 18 experimental runs were required for these study. The dimensions were measured by using digital smart scope machine. Experimental design matrix constructed according to standard order rule which was given in table II.

III. Result and Discussion

The experimental results as per the experimental plan are shown in table 2. These results were input into the Design Expert software version-7 [16] for further analysis. Without performing any transformation on the responses, the half normal plot Figure 1a and 1b revealed for the responses. The half normal plots shows the effects of factors and the factors lie along the line are negligible. Table III shows the significant factors (main and interaction factors) for the responses from the haft normal plots (figure 1a and 1b). The main effect B (injection pressure) is the most significant factor associated with the responses.

A. Analysis of Variance (ANOVA)

A ‘‘Model F value” is calculated from a model mean square divided by a residual mean square. It is a test of comparing a model variance with a residual variance. If the variances are close to the same, the ratio will be close to one and it is less likely that any of the factors have a significant effect on the response. As for a ‘‘Model P value”, if the ‘‘Model P value” is very small (less than 0.05) then the terms in the model have a significant effect on the response. Similarly, an ‘‘F value” on any individual factor terms is calculated from a term mean square divided by a residual mean square. It is a test that compares a term variance with a residual variance. If the variances are close to the same, the ratio will be close to one and it is less likely that the term has a significant effect on the response. Furthermore, if a ‘‘P value” of any model terms is very small (less than 0.05), the individual terms in the model have a significant effect on the response.

TABLE II: EXPERIMENTAL DESIGN MATRIX AND RESULTS

Run	Factors			Dimension (mm)	
	Mould Temperature	Injection Pressure	Screw Rotation Speed	Length	Width
1	95	2400	140	93.460	45.827
2	95	2250	140	93.448	45.822
3	95	2400	110	93.463	45.829
4	95	2250	140	93.449	45.824
5	85	2250	140	93.431	45.820
6	85	2400	140	93.445	45.824
7	95	2250	110	93.438	45.820
8	95	2400	110	93.463	45.829
9	90	2325	125	93.493	45.848
10	85	2400	110	93.451	45.823
11	95	2250	110	93.436	45.819
12	85	2400	110	93.448	45.823
13	95	2400	140	93.459	45.827
14	85	2250	110	93.422	45.815
15	90	2325	125	93.488	45.846
16	85	2250	110	93.427	45.814
17	85	2400	140	93.449	45.824
18	85	2250	140	93.432	45.817

TABLE III: THE SIGNIFICANT FACTORS EFFECT FOR THE RESPONSES.

Responses	Main Factors	Interaction Factors	Most Sig. Factor
Length	B, A and C	BC	B
Width	B, A and C	BC	B

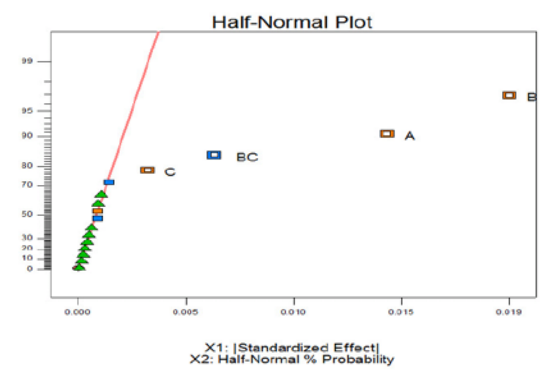

Figure 1a: Half normal plot for response length

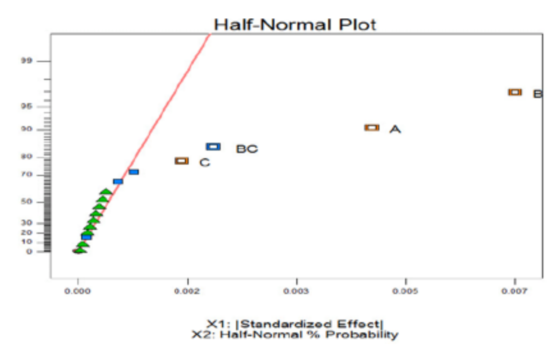

Figure 1b: Half normal plot for response width

The tables IVa and IVb show the resulting ANOVA for the improved models for the responses by selecting the backward elimination procedure in Design Expert software which will automatically reduce the terms that are not significant. The improved models show after the insignificant model terms removed. Table 4a shows the ANOVA result of the length. A ‘‘Model F value” of 134.99 with a ‘‘Model P value” of less than 0.0001 implies that the selected model is significant. A ‘‘P value” for the model term ‘‘A” (the mould temperature) and “B” (the injection pressure) are less than 0.0001 and “C” (the injection speed) is 0.0127, which is less than 0.05, indicating that the model term ‘‘A”, “B” and “C” are significant. Additionally, an interaction terms ‘‘BC”, also have significant influences to the length. Table IVb shows the ANOVA result of the width. A ‘‘Model F value” of 64.12 with a ‘‘Model P value” of less than 0.0001 implies that the selected model is significant. A ‘‘P value” for the model term ‘‘A” and ‘‘B” are less than 0.0001 and “C” is 0.0113, which are less than 0.05, indicating that the model term “A”, “B” and ‘‘C” are significant. Additionally, an interaction term ‘‘BC”, also have significant influences to the width.

TABLE IVA: ANOVA FOR RESPONSE LENGTH

Sum of Source	Squares	Mean df	F Square	p-value Value	Prob > F
Model	2.461E-003	4	6.152E-004	134.99	< 0.0001
A	7.701E-004	1	7.701E-004	168.97	< 0.0001
B	1.502E-003	1	1.502E-003	329.49	< 0.0001
C	3.906E-005	1	3.906E-005	8.57	0.0127
BC	1.501E-004	1	1.501E-004	32.93	< 0.0001
Curvature	3.670E-003	1	3.670E-003	805.38	< 0.0001
Residual	5.469E-005	12	4.557E-006		
Lack of Fit	1.369E-005	3	4.562E-006	1.00	0.4357
Pure Error	4.100E-005	9	4.556E-006		
Cor Total	6.186E-003	17			
Std. Dev.	2.135E-003		R-Squared	0.9783	
Mean	93.45		Adj R-Squared	0.9710	
C.V. %	2.284E-003		Pred R-Squared	0.9446	
PRESS	1.393E-004		Adeq Precision	54.107	

TABLE 4B: ANOVA FOR RESPONSE WIDTH

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	3.033E-004	4	7.581E-005	64.12	< 0.0001
A	8.556E-005	1	8.556E-005	72.37	< 0.0001
B	1.891E-004	1	1.891E-004	159.91	< 0.0001
C	1.056E-005	1	1.056E-005	8.93	0.0113
BC	1.806E-005	1	1.806E-005	15.28	0.0021
Curvature	1.084E-003	1	1.084E-003	916.45	< 0.0001
Residual	1.419E-005	12	1.182E-006		
Lack of Fit	4.687E-006	3	1.562E-006	1.48	0.2845
Pure Error	9.500E-006	9	1.056E-006		
Cor Total	1.401E-003	17			
Std. Dev.	1.087E-003		R-Squared	0.9553	
Mean	45.83		Adj R-Squared	0.9404	
C.V. %	2.373E-003		Pred R-Squared	0.8936	
PRESS	3.379E-005		Adeq Precision	51.472	

B. Regression Models

Considering the most significant terms from ANOVA result of length and width the regression models can be developed. From Tables IVa and IVb, mathematic predicted models (Equations in term of actual factors) for the length and width can be shown as follows:

$$\text{Length} = +92.216 + (1.388 \times 10^{-3} * \text{Mould Temperature}) + (4.694 \times 10^{-4} * \text{Injection Pressure}) + (6.433 \times 10^{-3} * \text{Screw Rotation speed}) - (2.722 \times 10^{-6} * \text{Injection Pressure} * \text{Screw Rotation speed}) \qquad \text{(Eq. 1)}$$

$$\text{Width} = +45.393 + (4.625 \times 10^{-4} * \text{Mould Temperature}) + (1.639 \times 10^{-4} * \text{Injection Pressure}) + (2.250 \times 10^{-3} * \text{Screw Rotation speed}) - (9.444 \times 10^{-7} * \text{Injection Pressure} * \text{Screw Rotation speed}) \qquad \text{(Eq. 2)}$$

The ANOVA Tables IVa and IVb also show that the lack-of-fit for the responses are insignificant because the ‘‘P value” are more than 0.05. The other important coefficient R^2 in the resulting ANOVA tables IVa and IVb are defined as the ratio of the explained variation to the total variation. It is a measure of the degree of fit. When R^2 values are high, close to 1, the better the response model fits the actual data. The value of R^2 calculated in table IVa and IVb for this reduced models are over 0.95, reasonably close to 1, which is acceptable. It demonstrates that more than 95% of the variability in the data is explained by these models. It also confirms that these models provide an excellent explanation of the relationship between the independent factors and the responses. Furthermore, the values of predicted R^2 are in reasonable agreement with the values of adjusted R^2. The adjusted R^2 value is particularly useful when comparing models with different number of terms. The values of adequate precision compare the range of the predicted values at the design points to the average prediction error. A ratio greater than 4 is desirable. In this particular case the values are well above 4.

C. Examine main effect and interactions

Figure 2a – 2d show that the effect main and interaction factor effect with responses length and width. In the interaction graph those points that have non overlapping intervals are significantly different and the points overlapping intervals not significantly different. Even though the interaction figure 2a – 2d show that there are significant effect on the responses at certain point but actually does not have any significant effect on the responses because the gradient of all the lines in figure 2a – 2d almost horizontal.

Tables V very clearly show that the gradient for all the lines are very close to zero. Due to that the responses do not have any significant different at high (+) or low (-) level of factors to increase the current dimensions to the target values. Therefore economically it is very clear that the response dimensions can be maintained close to target values by setting the injection machine parameters mould temperature, injection pressure and screw rotation speed at the lower level (A-, B- and C-). The same observation and decision can also be made from the 3D surface graphs shown in figure 3a – 3b.

But if look carefully the figure 2a - 2d it is clear that the most nearest points (Design Points) to the target values of the responses are obtainable when the factors A, B and C are at middle of the experimented range, that is when A, B and C are at 0 level. The same observation can also be made from the 3D surface graphs which are shown in figure 3a – 3b. Therefore the authors decided that in theory the response dimensions can be maintained close to target values by setting the injection process parameters mould temperature, injection pressure and screw rotation speed at the lower level (A-, B- and C-) but practically the experiment show that the middle or center parameter setting (A = 90 °C, B = 2325 km/cm^2 and

C = 125 mm/sec) is the optimised process parameters setting to achieve the target dimensions for the responses.

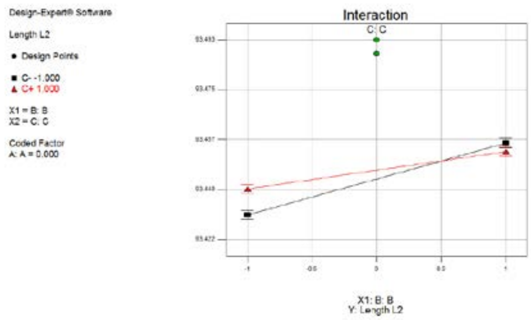

Figure 2a: Interaction graph of B versus C for Length.

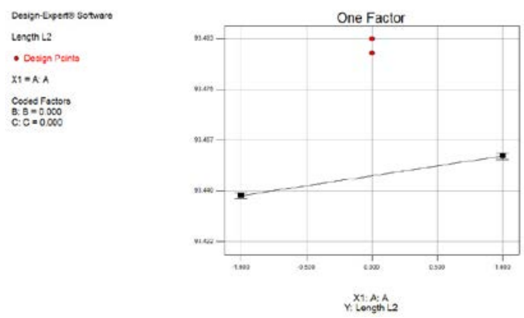

Figure 2b: Main factor A effect for Length

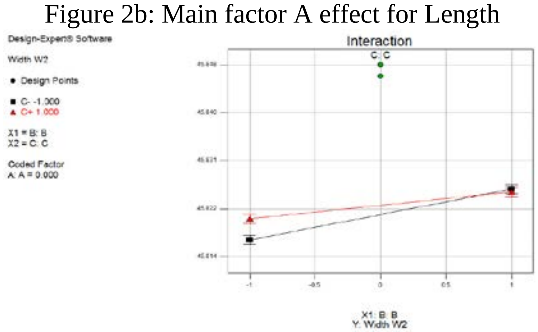

Figure 2c: Interaction graph of B versus C for Width.

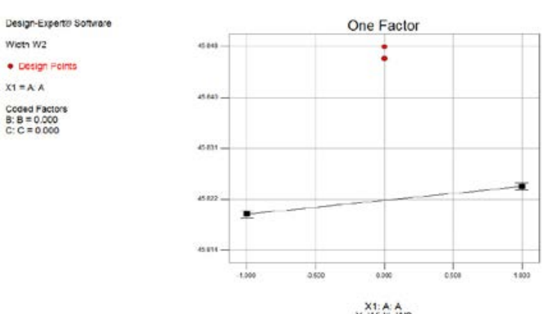

Figure 2d: Factor A effect for Width.

Table V: Gradient for the main and interaction effect for responses.

Response	Main Effect or Interaction	Gradient Line 1	Gradient Line 2
Length	BC	0.000	0.000
Length	A	0.001	N/A
Width	BC	0.000	0.000
Width	A	0.001	N/A

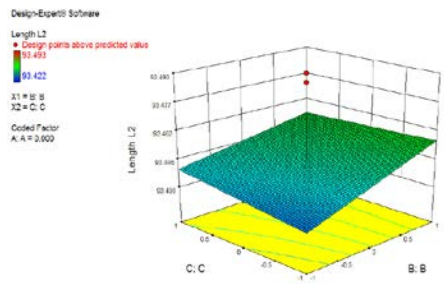

Figure 3a: 3D view B versus C interaction for Length.

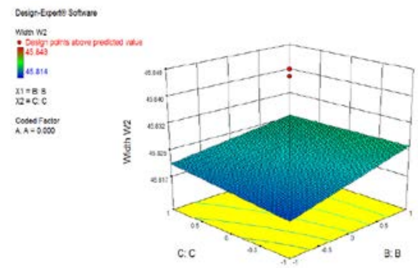

Figure 3b: 3D view B versus C interaction for Width.

D. *Confirmation Run*

Before switch to entire manufacturing operation to produce high volume of parts, need to do some verification runs with the above recommended parameter setting. The authors decided to produce 25 samples for the verification run. A different lot Polycarbonate (PC) material was used in this verification run. The purpose of this verification run was to validate that the center parameter setting where mould temperature is 90 °C, injection pressure is 2325 km/cm^2 and injection speed is 125 mm/sec is the optimised process parameters setting to achieve the target dimension. The control charts (figure 4a – 4b) shows clearly the upper, lower and central specification limit for the responses. The figures also show that the dimension of the 25 samples of length and width are within the specification limit 93.49 ± 0.2 mm and 45.93 ± 0.2 mm respectively and the values are near to target values of the length and width (93.49 mm and 45.93 mm respectively). The quality engineer from the team also confirms that the 25 samples were without other defect by visual inspection.

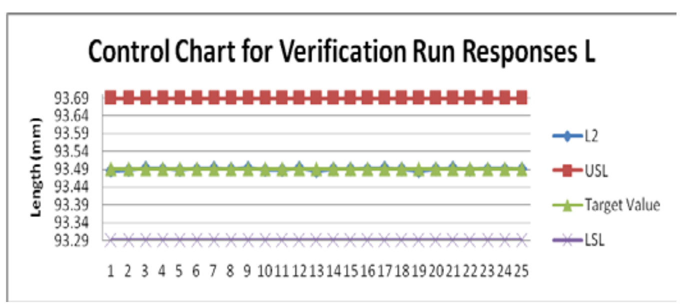

Figure 4a: Verification Run for response Length

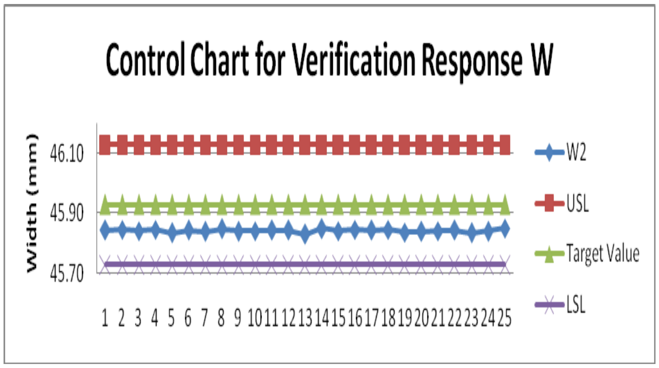

Figure 4b: Verification Run for response Width

IV. Conclusion

In this paper a DOE approach (2-level factorial design with center point) for optimising the injection moulding process was investigated. The injection moulding process parameters which will affect the dimensions (length and width) in a plastic cell phone shell studied. The significant factors affecting the length and width of the cell phone shell were identified from ANOVA. The optimal process parameters to maintain the dimensions closest to the target value were identified (mould temperature is 90 °C, injection pressure 2325 km/cm^2 and screw rotation speed is 125 mm/sec) from interaction graphs and 3D views. Statistical results and analysis are used to provide better interpretation of the experiment. The models are form from ANOVA and the models passed the tests for normality and independence assumptions. Confirmation run with the above center parameter setting determined that target dimensions for responses length and width were achievable. It is noted here that the results obtained in this study were quite satisfactory for the concerned industry since they were able to achieve the target values for the length and width of cell phone shell.

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