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Analysis of Optimal Injection Moulding Process Parameters for Thin-Shell Plastic Product Using Response Surface Methodology

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Abstract: The injection molding process is used to produce thin-walled plastic products for a wide variety of applications. However, the difficulty in adjusting optimum process parameters setting may cause defects on injected moulded parts such as shrinkage. A study was conducted for the determination of the optimal injection moulding process parameters which will minimize the shrinkage defect on a thin-shell plastic product for cell phone housing component. The machine process setting in use currently caused shrinkage where variations in the dimensions of the length and width below the specification limit. Therefore the experiment is needed to identify the optimal process parameters that could be set to maintain the length and width dimensions closest to the target value with smallest possible variation. The process parameters selected in this study are the mould temperature, injection pressure and screw rotation speed. The Response Surface Method (RSM) of analysis was used for the determination of the optimal moulding process parameters. The significant factors affecting the responses were identified from ANOVA. Statistical results and analysis are used to provide better interpretation of the experiment. Verification runs with the optimal process parameter setting found by RSM determined that the shrinkage defect can be minimized.

Key words: Thin-walled plastic, moulding defects, shrinkage defects, moulding process parameters

INTRODUCTION

Injection molding is suitable for mass-production of plastic products of complex shapes requiring precise dimensions. The injection molding process is used to produce thin-walled plastic products for a wide variety of applications, one of the most common being plastic housings. Plastic housing is a thin-walled enclosure, often requiring many ribs and bosses on the interior (Subramanian and Seng, 2005). The injection molding process requires the use of a mold, an injection molding machine and raw plastic material (Zema *et al*., 2012). The injection molding machine consists of two basic parts, an injection unit and a clamping unit. The entire injection moulding cycle can be divided into four stages: Plasticization, injection, packing and cooling (Tootoonchi, 2011).

Optimal process parameters setting is considered as one of the most important steps in injection moulding for improving the quality of moulded products (Shen *et al*., 2007). Previously, production engineers used either the trial-and-error method or one-factor-at-a-time (OFAT) method to determine the moulding optimal process parameters setting. These methods are time consuming, costly and needs to be repeated for each specific material, mould and machine configuration (Shie, 2008).

The Response Surface Method (RSM) was used to optimize the quality characteristics by determining the most appropriate and accurate moulding process parameters setting (Yacoub and MacGregor, 2003). Wu *et al*. (2012) studied the moulding process parameters in manufacturing of plastic bra-cups, whereby the optimal process parameters setting was determined by evaluating the main and interaction effects by RSM, to obtain a desirable response. Mathivanan and Parthasarathy (2009) developed a nonlinear mathematical model of injection molding parameters to determine the optimal process parameters using RSM. Chuang *et al*. (2009) applied RSM to determine the optimal parameters of injection molding process for manufacturing thin-shell plastic parts. Lin *et al*. (2010) applied RSM to discuss variation of mechanical characteristics depending on injection molding in the production of Short Glass Fibre (SGF) and Polytetrafluoroethylene (PTFE) reinforced Polycarbonate (PC) composites. Ozcelik and Erzurumlu (2006) minimized the warpage of thin shell plastic parts by integrating RSM and GA methods. Kurtaran and Erzurumlu (2006) proposed effective warpage minimization by using a

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combination of RSM, GA and ANN methods. Some of application of RSM was also applied in various process parameters optimization (Kumar *et al*., 2006; Rajin *et al*., 2007; Yan *et al*., 2009).

In this study, a case study was used to determine the optimal injection molding process parameters setting to minimize the shrinkage defect of the plastic cell phone housing (hereafter referred to as the plastic front cover) by using the RSM. The current injection molding process parameters are set by trial-and-error approach which could not maintain the length and width of the front cover within the specified limits due to shrinkage defect. The specified limits for the length and width without shrinkage are 93.49±0.2 and 45.93±0.2 mm, respectively. The target dimensions for the length and width are 93.49 and 45.93 mm, respectively.

METHODOLOGY

The Full Factorial Design (FFD) with Center Point (CP) experimental study was applied to determine the optimal process parameters setting which could be set to maintain the dimensions of the responses as close to the target values as possible. Subsequently, an approximate first-order model was developed if the curvature is insignificant as:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon$$

where, y is the response variable, x_i are the factors, β_0, β_i are the coefficients, k is the number of factors and ε is the experimental error.

If the curvature is significant, the RSM via Central Composite Design (CCD) experimental study was applied to determine the optimal process parameters setting which could be set to maintain the dimensions of the responses as close to the target values as possible. Subsequently, an approximate second-order model was developed as:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i<j}^{k} \beta_{ij} x_i x_j + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \varepsilon$$

where, y is the response variable, x_i and x_j are the factors, β_0, β_i are the coefficients for main effects, β_{ii} is the coefficients for quadratic main effects, β_{ij} is the coefficients for two factor interaction effects, k is the number of factors and ε is the experimental error.

Table 1: Critical injection moulding process, factors and their levels

	Level		
Factors	Low (-1)	Center (0)	High (+1)
A (°C)	85	90	95
B (kg cm^{-2})	2250	2325	2400
C (mm sec^{-1})	110	125	140

Experimental procedure: The identified critical factors were the mould temperature (A), injection pressure (B) and screw rotation speed (C) and their levels are shown in Table 1. The levels of the factors determined according to our experience about the process and from the literature research. The identified critical factors were studied at their high, center and low levels. The center point is equal to the average value of high and low level of the factor. The length and width of the front cover were identified as the two measurable responses. The number of runs needed according to 2^k FFD for three factors (k = 3) was eight ($(2)^3$) and the each run was repeated twice and the author wanted 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 this experiment.

The same critical factors (k = 3) are selected for RSM via CCD experimental study if curvature is significant. The design would consist of 8 corner points runs of cube, 6 axial runs, 6 center points runs (recommended by author) and the distance of the axial runs from the design centre will be calculated by the software. Therefore, a total of 20 experimental runs were required for this experimental study.

Statistical analysis: The experimental results and analysis obtained for the case study were analyzed by Design-Expert, (Ver.7) software.

RESULTS AND DISCUSSION

The FFD with CP experimental study results are shown in Table 2.

Table 2: FFD with CP experimental results

	Factors			Responses	
Random order	A	B	C	Length	Width
1	+1	+1	+1	93.470	45.822
2	+1	-1	+1	93.440	45.813
3	+1	+1	-1	93.455	45.823
4	+1	-1	+1	93.443	45.813
5	-1	-1	+1	93.429	45.800
6	-1	+1	+1	93.443	45.810
7	+1	-1	-1	93.428	45.815
8	+1	+1	-1	93.456	45.822
9	0	0	0	93.487	45.844
10	-1	+1	-1	93.442	45.821
11	+1	-1	-1	93.427	45.812
12	-1	+1	-1	93.441	45.820
13	+1	+1	+1	93.468	45.820
14	-1	-1	-1	93.426	45.810
15	0	0	0	93.486	45.844
16	-1	-1	-1	93.428	45.810
17	-1	+1	+1	93.441	45.808
18	-1	-1	+1	93.428	45.800

The half normal plots (Fig. 1 and 2) revealed for the responses (length and width). The half normal plots show the effects of factors and a line fitting is drawn through the effects that are close to zero. The factors lying along the fitting line are negligible and insignificant. It indicates that the injection pressure (B) is the most significant factor associated with the responses (length and width).

The ANOVA results for the improved model of the responses (length and width) are shown in Table 3 and 4, respectively. These tables 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 tables show that:

- The "p-value" of the responses models length and width are less than 0.0001; it indicates that the selected models are significant. Table 3 and 4 show that "p-value" for the main term A, B and C are less than 0.05, it indicates that the main term A, B and C are significant factor for the both responses. The tables also show that "p-value" for the interaction term AB and AC for length and AC for width are less than 0.05; it indicates that these interaction main terms are significant factor for the length and width, respectively
- The "p-values" for Lack-of-Fit of the responses models of length and width are more than 0.05; its indicates that the "Lack-of-Fit" is insignificant relative to the pure error which may contributed by the fixed injection moulding process parameters,

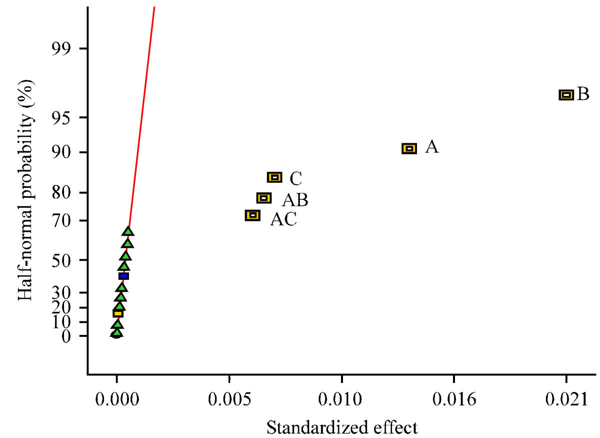

Fig. 1: Half normal plot for response length

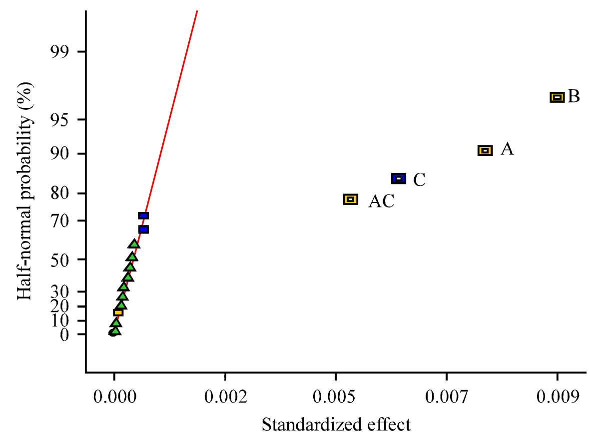

Fig. 2: Half normal plot for response width

Table 3: ANOVA for the response length

Source	Sum of squares	df	Mean square	F-value	p-value
Model	3.05E-03	5	6.11E-04	493.25	<0.0001
A	7.43E-04	1	7.43E-04	599.50	<0.0001
B	1.74E-03	1	1.74E-03	1407.24	<0.0001
C	2.18E-04	1	2.18E-04	175.65	<0.0001
AB	1.89E-04	1	1.89E-04	152.64	<0.0001
AC	1.63E-04	1	1.63E-04	131.24	<0.0001
Curvature	3.59E-03	1	3.59E-03	2898.35	<0.0001
Residual	1.36E-05	11	1.24E-06		
Lack of fit	6.25E-07	2	3.13E-07	0.22	0.8095
Pure error	1.30E-05	9	1.44E-06		
Cor. total	6.66E-03	17			

Table 4: ANOVA for the response width

Source	Sum of suares	df	Mean square	F-value	p-value
Model	7.99E-04	4	2.00E-04	188.87	<0.0001
A	2.33E-04	1	2.33E-04	219.96	<0.0001
B	3.33E-04	1	3.33E-04	315.01	<0.0001
C	1.38E-04	1	1.38E-04	130.58	<0.0001
AC	9.51E-05	1	9.51E-05	89.91	<0.0001
Curvature	1.63E-03	1	1.63E-03	1544.99	<0.0001
Residual	1.27E-05	12	1.06E-06		
Lack of fit	3.19E-06	3	1.06E-06	1.01	0.4337
Pure error	9.50E-06	9	1.06E-06		
Cor. total	2.44E-03	17			

Table 5: RSM via CCD experimental results

		Actual factors			Responses	
Random order	Type	A	B	C	Length	Width
1	Center	0	-1	0	93.488	93.494
2	Fact	+1	+1	-1	93.458	93.464
3	Axial	0	+1.682	0	93.452	93.460
4	Fact	-1	+1	+1	93.443	93.445
5	Axial	0	0	-1.682	93.446	93.448
6	Fact	+1	+1	+1	93.445	93.469
7	Axial	+1.682	0	0	93.468	93.472
8	Fact	-1	-1	-1	93.429	93.434
9	Fact	+1	-1	+1	93.440	93.447
10	Axial	0	0	+1.682	93.432	93.451
11	Fact	-1	+1	-1	93.443	93.449
12	Fact	-1	-1	+1	93.423	93.430
13	Center	0	0	0	93.487	93.490
14	Center	0	0	0	93.490	93.490
15	Center	0	0	0	93.490	93.491
16	Fact	+1	-1	-1	93.457	93.441
17	Axial	0	-1.682	0	93.436	93.430
18	Axial	-1.682	0	0	93.441	93.444
19	Center	0	0	0	93.491	93.492
20	Center	0	0	0	93.488	93.493

Table 6: ANOVA for response length

Source	Sum of squares	df	Mean square	F-value	p-value
Model	1.05E-02	9	1.17E-03	715.15	<0.0001
A	8.45E-04	1	8.45E-04	518.20	<0.0001
B	3.28E-04	1	3.28E-04	201.09	<0.0001
C	2.60E-04	1	2.60E-04	159.26	<0.0001
AB	9.80E-05	1	9.80E-05	60.12	<0.0001
AC	7.20E-05	1	7.20E-05	44.17	<0.0001
BC	1.25E-05	1	1.25E-05	7.67	0.0198
A^2	2.22E-03	1	2.22E-03	1359.56	<0.0001
B^2	3.74E-03	1	3.74E-03	2295.37	<0.0001
C^2	4.61E-03	1	4.61E-03	2826.63	<0.0001
Residual	1.63E-05	10	1.63E-06		
Lack of fit	4.30E-06	5	8.60E-07	0.36	0.8577
Pure error	1.20E-05	5	2.40E-06		
Cor. total	1.05E-02	19			

mould parameters, ambient conditions, human factors, etc. It also shows that the contributions in the factors-response relationship are accounted for by the models. Therefore, insignificant "Lack-of-Fit" is desired

- The ‘‘p-value" for curvature of the responses models of length and width are less than 0.0001 implies that the curvatures are significant for the responses in the design space. This means that the difference between the mean response of the centre points runs and the mean response of the factorial points are significant

Since the ANOVA analysis reveals the significant of curvature test for responses, an appropriate second order experimental design need to apply to continue the study to determine the optimal injection moulding process parameters setting. Therefore, RSM via CCD was applied as a second order experimental design to determine the optimal injection moulding process parameters setting.

The RSM via CCD experimental study results are shown in Table 5.

Table 6 and 7 show the ANOVA results for the improved models for the responses (length and width), respectively by selecting the backward elimination procedure in Design-Expert software which will automatically reduce if there are any terms that are not significant:

- The "p-value" of the responses models length and width are less than 0.0001; it indicates that the selected models for the respective responses are significant
- Table 6 shows the "p-value" for the main term A, B and C are less than 0.0001, indicating that the main term A, B and C are significant. In the same manner, the interaction terms AB, AC and BC and the quadratic terms A^2, B^2 and C^2 also significant model terms

Table 7: ANOVA for response width

Source	Sum of squares	df	Mean square	F-value	p-value
Model	3.19E-03	8	3.99E-04	183.75	<0.0001
A	2.31E-05	1	2.31E-05	10.66	0.0075
B	3.12E-04	1	3.12E-04	143.60	<0.0001
C	8.28E-07	1	8.28E-07	0.38	0.5492
AB	5.00E-05	1	5.00E-05	23.05	0.0006
BC	1.25E-05	1	1.25E-05	5.76	0.0352
A^2	1.49E-03	1	1.49E-03	688.03	<0.0001
B^2	1.02E-03	1	1.02E-03	469.77	<0.0001
C^2	8.16E-04	1	8.16E-04	376.21	<0.0001
Residual	2.39E-05	11	2.17E-06		
Lack of fit	1.05E-05	6	1.76E-06	0.66	0.6895
Pure error	1.33E-05	5	2.67E-06		
Cor. total	3.21E-03	19			

Table 8: ANOVA summary statistics of quadratic model for responses

Responses	R^2	Adjusted R^2	Predicted R^2	Adequate precision
Length	0.9984	0.9971	0.9952	72.296
Width	0.9926	0.9872	0.9758	36.125

- Table 7 shows the ''p-value'' for the main term A and B are less than 0.0001; indicating that the main term A and B are significant. However, the individual main term C was added to support hierarchy. In the same manner, the interaction terms AB and BC and the quadratic terms A^2, B^2 and C^2 also significant model terms
- The "p-values" for "Lack-of-Fit" of the responses models of length and width are more than 0.05; it indicates that the lack-of-fit is insignificant relative to the pure error which might have been contributed by moulding process parameters, mould parameters, ambient conditions, human factors, etc. It also shows that the contributions in the factor response relationship are accounted for by the models. Therefore, non significant Lack-of-Fit is desired

ANOVA summary statistics of improved quadratic model for responses are shown in Table 8. All the R^2 values, namely, R^2, adjusted R^2 and predicted R^2 values are high and close to one which is desirable.

The result indicates a good correlation between the predicted and actual response value. This comparison is however done in the background when model reduction is taking place. The difference between values of adjusted and predicted R^2 that is less than 0.2, shows them to be in agreement. Since all adequate precision of all models are more than four indicate adequate model discrimination. In this particular case the values are well above four.

The predicted model equations based on coded factors for the responses length and width are shown, where A, B and C are the mould temperature, injection pressure and screw rotation speed respectively. The equations show the improved models after the insignificant model terms are removed:

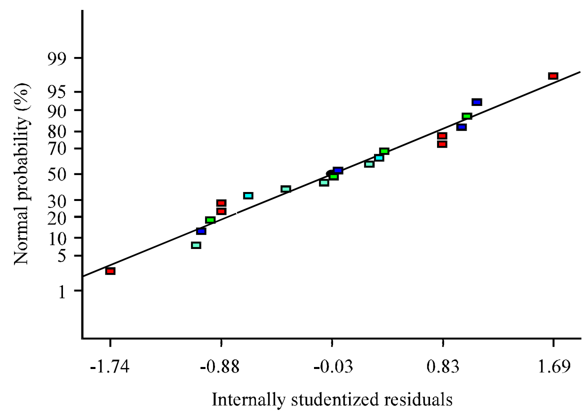

Fig. 3: Normal probability plot for length

$$\text{Length} = +9.35E{+}01+7.86E{-}03\times A+4.90E{-}03\times B-4.36E{-}03\times C-3.50E{-}03\times AB-3.00E{-}03\times AC+1.25E{-}03\times BC-1.24E{-}02\times A^2-1.61E{-}02\times B^2-1.79E{-}02\times C^2$$

$$\text{Width} = 4.58E{+}01+1.30E{-}03\times A+4.78E{-}03\times B-2.46E{-}04\times C-2.50E{-}03\times AB-1.25E{-}03\times BC-1.02E{-}02\times A^2-8.41E{-}03\times B^2-7.53E{-}03\times C^2$$

Model adequacy can be checked by residual analysis:

- Normal probability plots of residuals for the predicted quadratic models are shown in Fig. 3 and 4. According to the normal probability plots, the distribution of the residuals falls along a straight line indicating that the error distributions for the responses (length and width) data are almost normal. As a result, the models are sufficient
- Response residuals versus predicted plots in Fig. 5 and 6 revealed that all data presented are in the range and no abnormal trends were observed.

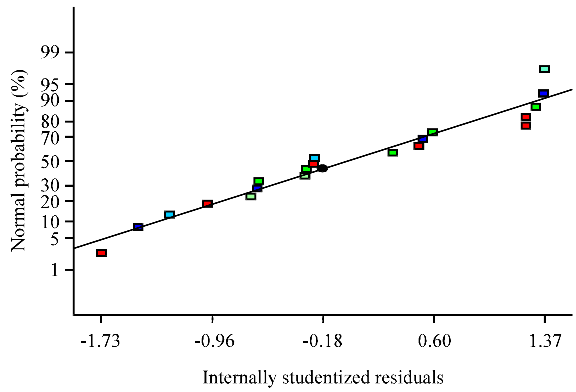

Fig. 4: Normal probability plot for width

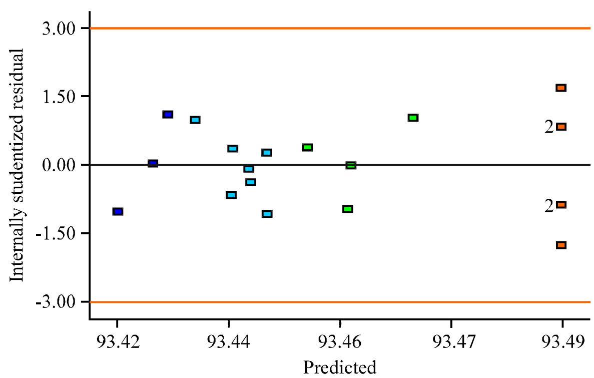

Fig. 5: Plot of response length residuals vs. predicted

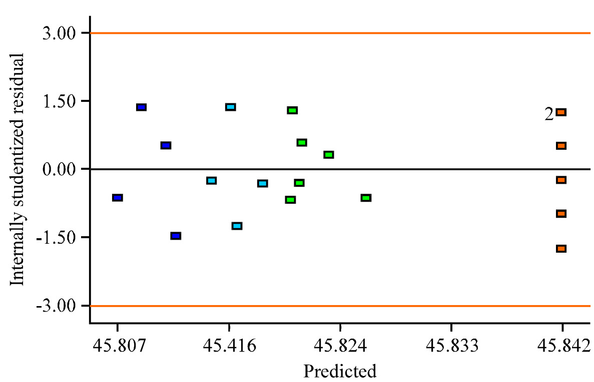

Fig. 6: Plot of response width residuals vs. predicted

Almost all residuals were distributed between -1.5 and +1.5 without having any systematic structure. This implies that all the predicted models proposed (length and width) are adequate and there is no reason to suspect any violation of the independence or constant variance assumption

Determine the optimal injection moulding process parameters setting.

- Figure 7a and b indicate the changes in the response surface of length. The length shows an upward trend when the moulding temperature (A) is increased from 85°C to around 90°C and injection pressure (B) from 2250 kg cm^{-2} to around 2331 kg cm^{-2}, when the screw rotation speed (C) was fixed at 123 mm sec^{-1}. As indicated by the contours, the length reach the target value of 93.49 mm. If the moulding temperature (A) and injection pressure (B) exceed the above values simultaneously, the maximum value for length will be achieved and thereafter will emerge a decline. The pattern of the contours reveals that the predicted target value for length which is 93.49 mm can be achieved by setting the injection moulding process parameters; moulding temperature (A) and injection pressure (B) at 90° and 2331 kg cm^{-2}, respectively, when the screw rotation speed (C) is 123 mm sec^{-1}
- Figure 8a and b indicate the change in the response surface of width. The width shows an upward trend when the moulding temperature (A) is increased from 85°C to around 90°C and injection pressure (B) from 2250 kg cm^{-2} to around 2331 kg cm^{-2}, when the screw rotation speed (C) was fixed at 123 mm sec^{-1}. As indicated by the contours, the width reaches the maximum value around 45.84 mm. If the moulding temperature (A) and injection pressure (B) exceed the above values simultaneously, there will emerge a decline in the width. The response surface shape also shows that the width can never be reached the target value which is 45.93 mm with even a higher or lower injection pressure or moulding temperature. Therefore, it is predicted that the maximum value for width which is around 45.85 mm is achievable by setting the injection moulding process parameters; moulding temperature (A) and injection pressure (B) at 90°C and 2331 kg cm^{-2}, respectively, when the screw rotation speed (C) is 123 mm sec^{-1}

Validation runs-before switch to mass production, need to do verification runs with the above predicted optimal process parameter setting. The authors decided to produce 25 samples for the verification run. The control charts (Fig. 9 and 10) show the measurement for the responses of the 25 continuous shots with clear identification of upper, lower and target limits for the respective responses. The figures show that the dimensions of the 25 samples of the respective responses are within the specification limits. As predicted, the

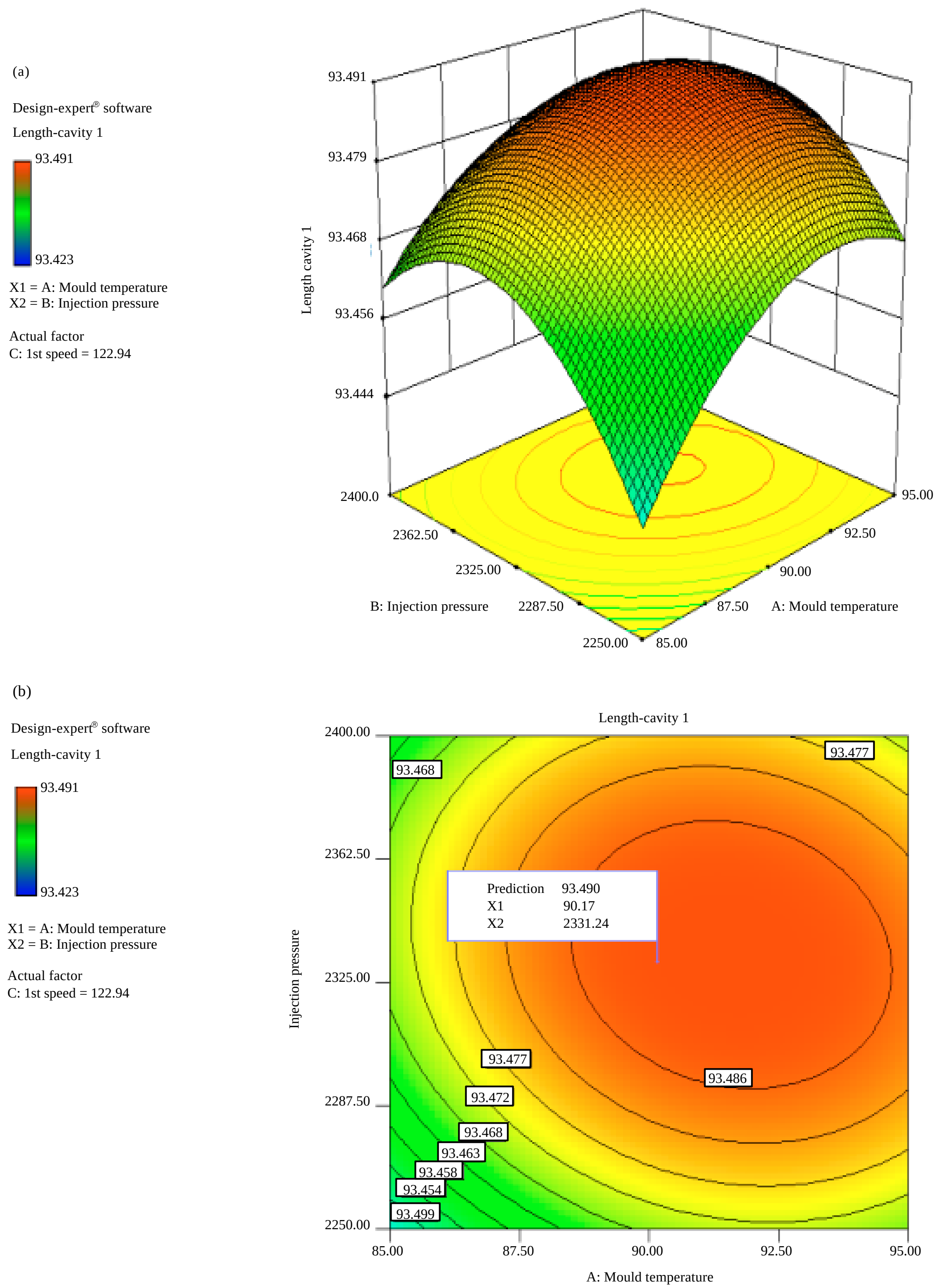

Fig. 7(a-b): (a) Response surface and (b) Contour plot for length (Screw rotation speed = 123 mm sec^{-1})

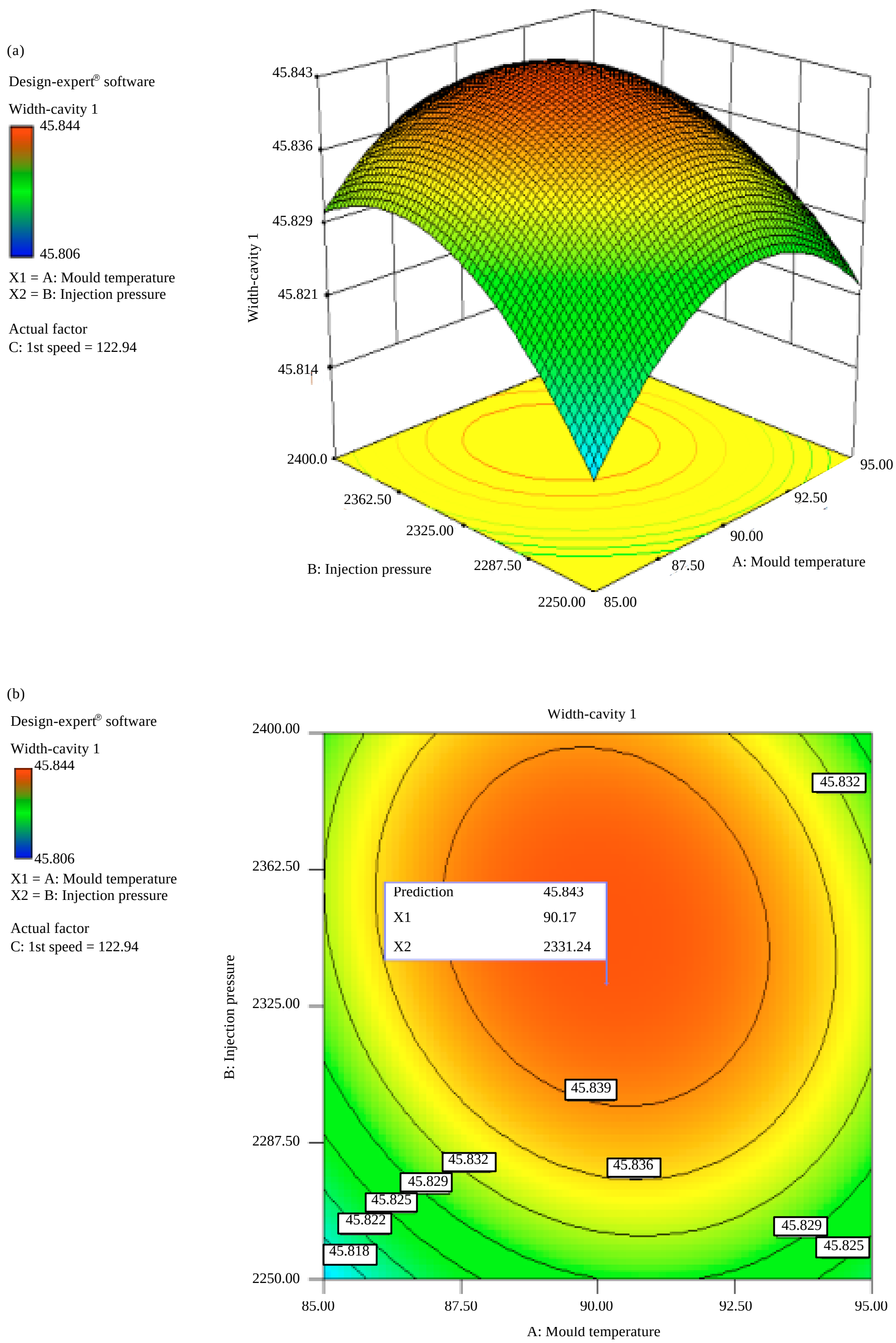

Fig. 8(a-b): (a) Response surface and (b) Contour plot for width (Screw rotation speed = 123 mm sec^{-1})

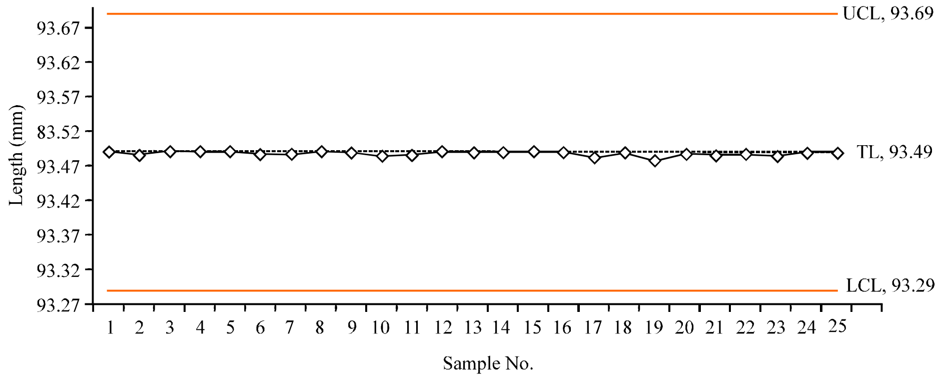

Fig. 9: Measurement of response length from verification runs

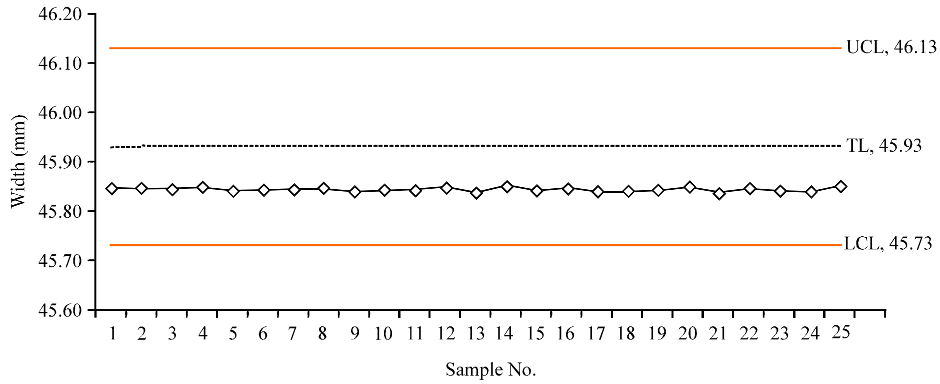

Fig. 10: Measurement of response width from verification runs

figures also show that the target value of length (93.49 mm) can be achieved and can be maintained by the redicted optimal injection moulding process parameters setting. At the same time, it also shows the target value for the width (45.93 mm) can never be achieved. But, at least it can be maintained around 45.85 mm.

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