Investigating Red X Parameter for Short Shot-Type Defect in Plastic Injection Moulds Using Shainin's Design of Experiments

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Abstract The study has investigated key parameter(s), which causes short shot-type defect in the case of a plastic injection moulding process using Shainin DoE methodology. An average rejection rate of around 11% was recorded over a period of three months, due to the presence of short shot-type defect for a bulb holder component (E27). Shainin's DoE methodology of Red X, based on progressive elimination search principle, was adopted to identify key parameter (s), which caused such defect among the variables selected for the study. Selective tools from Shainin's DoE methodology were adopted and a particular variation reduction roadmap was prepared to investigate the process. The influential factor identified was the injection time, a solid Red X, i.e. a dominant variation causing variable.

Keywords Product/process search · Variable search · Shainin approach

1 Introduction

Injection moulding is an important polymer processing operation in plastic industries. In this process, polymer is injected into a mould cavity and is allowed to solidify to the shape of the mould required. Optimizing the parameters of the injection moulding process is critically important to enhance the productivity of the process. Rejection rates will be larger, when design and process variables run at high variations from the required tolerance. Shainin as a design of experiments (DoE) tool put forth a statistical technique to control the variation and the philosophy involved is, 'Talk to the parts; they are smarter than the engineers'. Shainin DoE methodology is dominant, because it does not affect the on-line production and the data acquired from the production

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is analysed to spot the suspected source of variable (SSV) and variation for the respective SSV is reduced by optimizing the process parameters [1].

2 Literature Review

Khavekar et al. [2] used Shainin DoE method in their study to find SSV in aluminium casting process and found 86% reduction in the rework of the process. Khavekar et al. [3] compared two DoE methods and concluded that the Shainin Method is very easy to deploy on the shop floor. Khavekar et al. [4] deployed Shainin DoE in NVH testing in automotive industry to find unknown variable responsible for the vaibration. Kiatcharoenpol and Vichiraprasert [5] had used variable search method to find significant parameters affecting the quality of plastic products in their case study. According to them, less numbers of experiments are required in Shainin method and it can be applied for enhancing the quality of manufacturing process. Chitali and Rajiv [6] used Shainin method in their study to eliminate the oil leakage defects in V series diesel engines. Jagdheesson et al. [7] used Shainin's roduct search tool as a clue generating tool and B versus C as a validation tool in their case study to reduce the peak failure load of hot-staked joints in starter motor armature.

3 Problem Statement

An average rejection rate of around 11% was recorded over a period of three months in an injection moulding firm, due to the presence of short shot-type defect for a bulb holder component. Short shot-type defect could largely occur due to lower barrel temperature (zone1 and zone2), insufficient injection pressure, lesser injection time, inadequate degassing and flow of material. With the guidance of the experts in the firm, the parameters identified for analysis in the study were listed as in Table 1, as they could be regulated and controlled.

Short shot-type defect was consistently observed on the component mould. Pareto analysis was done to identify the defect-wise rejection as shown in Fig. 1 and it confirmed that short shot was the major defect observed. Green Y (response factor) selected was short shot-type defect for the component considered, which was of attribute nature.

Table 1 List of selected parameters for the study

Label	SSV	Level
A	Injection time	4 s
B	Injection pressure	48 bar
C	Zone 1 temperature	265 °C
D	Zone 2 temperature	260 °C

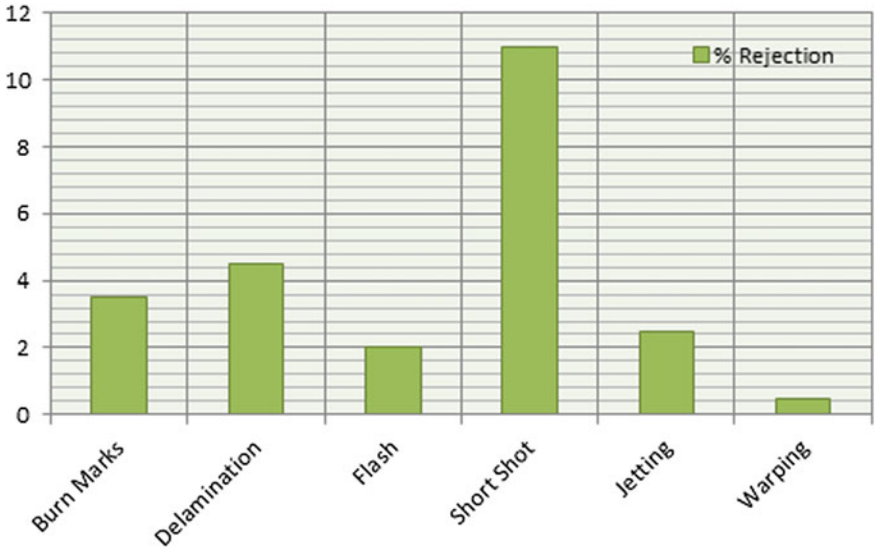

Fig. 1 Major defect by Pareto charting

4 Research Methodology

The first step was defining the problem by historic data. Clue generation tools assisted in identifying the influential SSV and preparing its list. Product/process search (PPS) was the tool selected for clue generation. Variable search (VS) was the formal DoE tool selected for pinpointing the Red X, Pink X and so on. Result validation was achieved by B versus C technique. Product/process search (PPS) separated the important process parameters from the unimportant ones. It followed the pattern of total end count calculation. From trials performed, a batch was selected, which contains 8 good parts & 8 bad parts. The combination of eight good parts and eight bad parts called worst of worst (WOW) and best of best batch (BOB). To identify the influential SSV, the data of each SSV was arranged in the ascending order and the total count (addition of top count and bottom count) with respect to Green Y was calculated. Counting of all batches was made. If the total count (TC) was greater than or equal to 6, then that SSV was the reason for the problem. If the total count was less than 6, then that SSV was not the reason for the problem.

Variable search technique of formal DoE selects the parameters from PPS, which are highly influential, i.e. significant factors with two levels; best (+) setting and marginal best (−) setting. Running the experiment with these settings and calculating the D/d ratio for each SSV were to pinpoint the critical SSV. D is the difference between the median values of the best and the marginal Green Y and d is the average of the two differences (or ranges) within the all best Green Y and the all marginal Green Y. If D/d ratio was greater than 1.25 for SSVs, it indicated that the right process parameters have been captured for analysis. The tool separated the important and unimportant parameters and pinpointed the actual Red X. Better versus current (B vs. C) technique was applied on SSV obtained from variable search method; it validated the trueness of Red X, measured by conducting the experiment again.

5 Experimental Work and Result

Readings were taken from four batches, each of batch size 50. From a total of 200 readings taken, eight good components and eight bad components were selected for the study as seen from Table 2, for the Green Y as short shot-type defect, as shown in Fig. 2.

After arranging each parameter values given in Table 2 in the ascending order, total end count was calculated. Product/process search (PPS) followed the pattern of total end count calculation and it separated important process parameters from unimportant ones. Total end count calculation, whose total count was ≥ 6 for the SSV, is as shown in Table 3.

PPS funnels down the number of SSV from 4 to 2 parameters. These two parameters were further analysed by variable search (VS) tool. With the help of the firm experts, the influential SSVs were set at two levels; best (+) setting and marginal best (−) setting as seen in Table 4, for starting the VS technique. In the VS method,

Table 2 Eight Best of best (BOB) and eight worst of worst (WOW) readings

S. No.	Reading No.	A	B	C	D	Response
1	121	6	50	270	262	B
2	152	6	50	271	261	B
3	69	4	48	268	260	B
4	46	4	48	272	258	B
5	123	6	50	270	262	B
6	49	4	48	271	259	B
7	192	6	50	269	259	B
8	188	6	50	268	258	B
9	11	4	48	266	260	W
10	55	4	48	269	259	W
11	44	4	48	269	261	W
12	72	4	48	268	262	W
13	25	4	48	272	258	W
14	62	4	48	271	259	W
15	29	4	48	270	259	W
16	59	4	48	269	260	W

Fig. 2 Component with short shot-type defect

Table 3 Calculation of total count (TC)

A	Response	B	Response	C	Response	D	Response
4	B	48	B	266	W	258	B
4	B	48	B	268	B	258	B
4	B	48	B	268	B	258	W
4	W	48	W	268	W	259	B
4	W	48	W	269	B	259	B
4	W	48	W	269	W	259	W
4	W	48	W	269	W	259	W
4	W	48	W	269	W	259	W
4	W	48	W	270	B	260	B
4	W	48	W	270	B	260	W
4	W	48	W	270	W	260	W
6	B	50	B	271	B	261	B
6	B	50	B	271	B	261	W
6	B	50	B	271	W	262	B
6	B	50	B	272	B	262	B
6	B	50	B	272	W	262	W
TC = 8		**TC = 8**		**TC = 3**		**TC = 2**	

Table 4 Influential process parameter obtained from PPS technique for Green Y with best (+) and marginal best (−) setting

Label	+ setting	− setting
A	6	4
B	52	48

Table 5 First run for VS technique

	All at +	All at −
	Green Y (results)	
Run 1	08	48

initially, running two experiments, first all factors at their best levels and second all factors at their marginal levels were taken as seen in Table 5.

For run 1, all at + settings:

Weighted defect score = number of defective units * defect-type Likert scale = 2 * 4 = 08

For run 1, all at − settings:

Weighted defect score = number of defective units * defect-type Likert scale = 6 * 8 = 48

As there was a large difference between the Green Y's of the all-best and the all-marginal combinations of factors, it gave an indication that the right list of factors was captured. Two more experiments were run with the same setting. This meant that, altogether; there were now three all-best and three all-marginal best levels as seen in Table 6.

For run 2, all at + settings:

Weighted defect score = number of defective units * defect-type Likert scale = 5 * 2 = 10

For run 2, all at − settings:

Weighted defect score = number of defective units * defect-type Likert scale = 7 * 8 = 56

For run 3, all at + settings:

Weighted defect score = number of defective units * defect-type Likert scale = 4 * 1 = 4

For run 3, all at − settings:

Weighted defect score = number of defective units * defect-type Likert scale = 8 * 6 = 48

As all three of the all-best Green Y's were better than all three of the all-marginal Green Y's, with no overlap, the first test of significance was cleared. Now, calculating the D/d ratio for second test of significance: $D = 40$ and $d = 7$, $D/d = 5.71$, which was greater than 1.25:1 indicated that the right process parameters have been captured for analysis. Both the tests of significance were passed, and it was concluded that right factors have been captured, even though the Red X, Pink X, etc., have not been

Table 6 All runs VS results

	All at +	All at −
	Green Y	
Run 1 (initial)	08	48
Run 2	10	56
Run 3	04	48

Table 7 Running each parameter at (+) and (−)

Test	Combination	Results	Median	Decision Limits	Conclusion
1	A−R+	42	8	−02.73 to 18.73	Complete reversal, Red X
2	A+R−	12	48	37.26 to 58.73	
3	B−R+	32	8	−02.73 to 18.73	Partial reversal, B important with another factor
4	B+R−	24	48	37.26 to 58.73	
5	C−R+	16	8	−02.73 to 18.73	C not important
6	C+R−	56	48	37.26 to 58.73	
7	D−R+	14	8	−02.73 to 18.73	D not important
8	D+R−	48	48	37.26 to 58.73	

pinpointed. Now, running a pair of tests for each parameter at (+) best setting and remaining all at (−) marginal best setting and vice versa was done as given in Table 7. Also, calculating the high side and low side of decision limits using the formula: The decision limits were: median $\pm$ (2.776 * d)/1.81.

As parameter C and D showed results inside the low side and high side of decision limits, factors C and D, along with all of its associate interaction effects, were considered unimportant and it could be eliminated from further study. As there was a complete reversal, i.e. A−R+ became the original all-best level and A+R− became the original all-marginal level, A was the only Red X. Parameter, A, i.e. injection time, was the solid Red X. Now, as both pairs of tests for factor B showed results outside the low side and high side of decision limits, respectively, but not a complete reversal, it could not be eliminated along with its associated interaction effects. Hence, there was definitely the presence of Pink X. On discussion with the firm experts in the firm, 5% risk allowance, i.e. confidence level of 95%, running six more trials, three samples of B and three samples of C were selected to validate the results using B versus C technique. The results of the three B tests, and three C tests, i.e. six pack tests are as given in Table 8. As seen from Table 8, testing was done in random order sequence (run order), the three B's outranked the three C's with 95% confidence (5% risk) and the tool validated the selected parameters.

Table 8 B versus C results

Run order		Rank order	
B or C	Results	B or C	Results
C	52	B	08
B	10	B	10
B	12	B	12
C	40	C	36
C	36	C	40
B	08	C	52

Table 9 Spotted SSV

Label	Label description	Remark
A	Injection time	Red X
B	Injection pressure	Pink X

Table 10 Optimized settings for parameters selected

Label	Label description	Optimized setting	Allowable variation
A	Injection time	6 s	–
B	Injection pressure	52 bar	–
C	Zone 1 temperature	265 °C	± 2 °C
D	Zone 2 temperature	260 °C	± 2 °C

6 Conclusion

Without disturbing the on-line production, Shainin's approach could be implemented easily in the study. Shainin envisages for process improvement using convergent strategies by reducing the variation causing variable(s) with progressive elimination search technique. Narrowing down the critical factor leads to uncomplicated experimental set-up and runs for changing factor levels. Validating and optimizing the process performance by Shainin tool-bag during full production run were of ease as the root cause was known.

Product/process search technique is funnelled down the factors to 2 using Tukey test of end count calculation. These two factors were further taken for study in variable search and the tool has successfully identified the Red X and Pink X and can be seen in Table 9.

The optimized setting obtained after applying Shainin's progressive elimination principle with the guidance of the firm experts can be seen in Table 10.

Shainin DoE is very easy to implement on the shop floor without changing the set-up of the manufacturing process.

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