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Application of Taguchi Method and Shainin DOE Compared to Classical DOE in Plastic Injection Molding Process

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Abstract: Design of Experiment (DOE) has prevailingly used in various industries from its effectiveness of a statistical technique for managing and improving processes. In this work, the three DOE approaches, Classical DOE or factorial design, Taguchi method and Shainin DOE are applied in a case of plastic injection molding process. A comparative analysis is carried out to express the way of implementation and the merit of each approach based on the accuracy of information and the ease of use. The results show that significant factors obtained from the three DOEs are aligned together. For all approaches, the most three factors influencing to the response, %volume shrinkage, are exactly the same including the optimal process parameters chosen. This is one of an evidence of effectiveness for both Taguchi method and Shainin DOE in practice. The adoption of DOE approaches outlined in this paper and their application to an industrial process will be valuable to practitioners to gain understanding of DOE techniques and to use them fit to their quality issue.

Keywords: Taguchi method, Shainin DOE, Experiment design, Plastic injection molding process.

1. Introduction

The field of industrial statistics has introduced a range of statistical methods for managing and improving processes in diverse industries [1, 2]. Statistically experimental design or Design of Experiments (DOE) is one of the powerful statistical tools for investigating deeply hidden causes of process variation in complex industry environment [3, 4]. The classical DOE or factorial design introduced by Sir Ronald in the application to agriculture research is one of common use in industry. By late 1970s, Taguchi method, a better potential to bring about break through improvements in manufacturing process is also proposed, but the methodology using novel statistical concepts such as orthogonal array, loss function and robust design. However, due to their complexity and theoretical imperfection, the success cannot be assured at every instance [5]. The need for simpler alternative for manufacturing experiment led to the development of Shainin DOE. It can improve the performance of product and process in industries with the amount reduction in experimental runs and cost by using process expertise and experience.

Although there are a number of literatures presenting applications of these DOE approaches, the implementation to solve a real world quality problem is not simple because of involvement of sophisticated statistic tools and variant methods. The work of Rajendra [6] supports that there is a need for comparative study of DOE approaches in manufacturing. It is also important to select an appropriate DOE approach for coping with varied processes as well as to identify the suitable DOE that could be used to improve the productivity of a product and process.

In this study, the three well-known DOE approaches, Classical or factorial design, Taguchi method and Shainin DOE are used in a case of plastic injection molding process. Since DOE is based on sophisticated statistic techniques and there is a variety of DOE approaches developed for specific environments, it is not so straightforward to be applied to real world industry processes, this study would help to elaborate their key concepts and important steps to ease practitioners for understanding of implementation. Firstly, Fractional factorial design is performed as a baseline comparison with both Taguchi method and Shainin DOE. After all DOEs are applied to a case study, a comparative analysis is summarized to practically describe the characteristics of these three DOE approaches in details. The results of the accuracy of information and the ease of implementation of this comparative study will provide a guideline for a selection of appropriate DOE.

2. Literature review

2.1 Taguchi method

It has been reported that Taguchi method is a very efficient problem solving statistical quality tool. It can improve the performance of the product, process, design and system in manufacturing companies, with a significant reduction in experimental time and cost using an orthogonal array [7]. This method also mixes the experimental design and quality loss function concept, which has been used for carrying out robust design of processes and products and solving very complex quality related problems in manufacturing. It is simply applicable in a wide range of industries [8, 9]. The use of Taguchi method involves with following steps [10]:

a) Identify the main function and it side effects,
b) Identify the noise factors, testing conditions, and quality characteristics,
c) Identify the objective function to be optimized,
d) Identify the control factors and their levels,
e) Select the orthogonal array matrix experiment,
f) Conduct the matrix experiment,
g) Analyze the data, predict the optimum levels and performance,
h) Perform the verification experiment and plan the future action.

2.2 Shainin DOE

Shainin DOE tools are very effective in manufacturing industries to solve the problem of process optimization. Within the DOE techniques, the Shainin DOE provides the simplest, easiest and most effective ways to get the solution [11]. It is also simple to be understood by both the engineers and shop floor workers since its logical based on basic science and engineering knowledge. Shainin method defines to the first most important factors as the “RedX”, the second as the “PinkX”, and then the third as “PalePinkX”. The methodology can be divided into four steps [12-14].

1) Identification of factors and decision limits

The objective is to determine and to select the right variable and the right levels for each factor for the experiment. According to the work of Verma [15], after selecting the factors for the experiment, they are assigned two levels to each factor-a best level, which is likely to contribute to a best response/output and a marginal level, indicative of a likely deviation from the best level. Once the factors and levels are fixed, two experimental groups are run, first group with all factors at their best levels, second group with all factors at their marginal levels. If there is a large difference between the response of the All-Best and the All-Marginal combinations of factors, it is an early indication that one has captured the right factors. If the difference in response is small, the chances are that one has not captured the right factors or the right levels of these factors. The final stage of this phase is to calculate the resulting ratio between D and d, which D is the difference between the median values of the best and the marginal responses and d is the average of two ranges. The technique states that the difference between the medians of the three replications in the experiments must exceed the average of the two ranges by a factor of at least 1.25 /1. It implies that correct factors have been captured, and then experimentation can be moved to the second step.

2) Separation of important and unimportant factors

The aim is to separate the critical factors from the non-critical factors and get rid of non-critical factors including interaction caused by the factor out. The experiment starts with switching factor of each pair and finding the highest and lowest value under the range of decision limits (high sides) and decision limits (low sides) by using a formula median + 2.776 $\bar{d}$ / 1.81 to be the decision limits.

3) Confirmation of significant factors

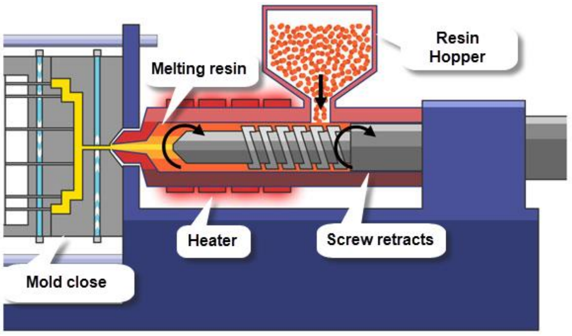
The objective of this process is to confirm an essential factor and the importance of factors. Besides, it is to verify whether or not the remaining unimportant factors in the experiment can be ignored which test confirmed the result of the factor and interaction by reversing the factors. A successful result is where the value obtained from experimentation falls within decision limits thus confirming that the factors identified are correct. At present, this allows the experimentation to progress to the factorial analysis step.

4) Factorial analysis and optimal setting

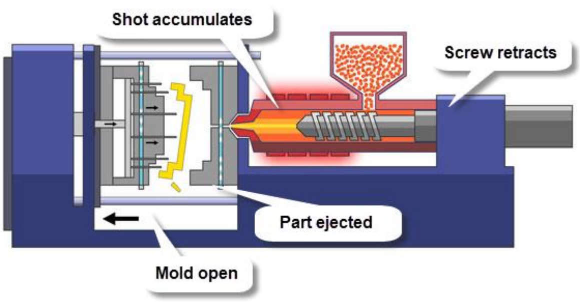
The objective is to analysis of key factors that will make the best process or product quality by determine the main and interaction effect. Shainin DOE recommends a graphical analysis called an interaction plot to see whether or not the factors are interacting a lot in order to the determination of the factors that will make the next best work-piece quality.

3 A case of plastic injection molding process

A case study conducted in this work is the plastic injection molding process, which is commonly found in most industry. The simulation software of injection process is used as an experiment rig to study various factors that might influent to quality of plastic work-piece. The objective of DOE studied is to investigate the factors that are significant to volume shrinkage of the work-piece. The injection molding processes in Fig. 1 are separated into four steps: 1) Plasticizing the resin, 2) Injecting the resin, 3) Cooling the part and 4) Ejecting the part. In the starting step, a screw will



(a)



(b)

Figure. 1 Injection molding processes: (a) plasticizing the resin and (b) ejecting the work-piece [16]

Table 1. Experimental factors and their levels

Factors	Level Low (-)	Level High (+)	units
A. Filling time	2	3	sec.
B. Melt temperature	215	230	°C
C. Mold temperature	35	60	°C
D. Maximum injection pressure	50	80	%
E. Packing time	4	6	sec.
F. Maximum packing pressure profile value	30	50	%
G. Cooling time	12	14	sec.
Uncontrollable Factors			
H. Air temperature	15	40	°C
J. Eject temperature	50	99	°C

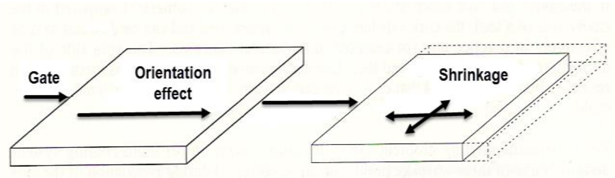


Figure. 2 Volume shrinkage of plastic work-piece

rotate and retract for melting in order to set plastic resin into ready liquid state. Then, liquid plastic is injected into the molding. Packing process will be done to maintain pressure in order to compensate for shrinkage of the plastic formation. A cooling process of work-piece is started until temperature of work-piece reach to the eject temperature and work-piece is loaded off of the molding [16].

The factors which are influent to the volume shrinkage are set into two groups. The first group has seven controllable process parameters and another group has two uncontrollable process parameters as presented in the table below:

The levels of all factors are set to cover the normal operation range of injection molding process as shown in Table 1. The two-level design is use in order to be fit for various DOE techniques that will be carried out later in this study.

The key response is the volume shrinkage of work-piece as shown in Fig. 2. This response is measured in percentage (%) by using a formula below:

$$\text{Volume shrinkage (\%)} = \frac{\text{size of mold cavity - size of work-piece}}{\text{size of mold cavity}} \times 100 \quad (1)$$

The software program is applied to analyze the injection molding process for finding the best value of work-piece design and the percentage of volume shrinkage as shown in Fig. 3.

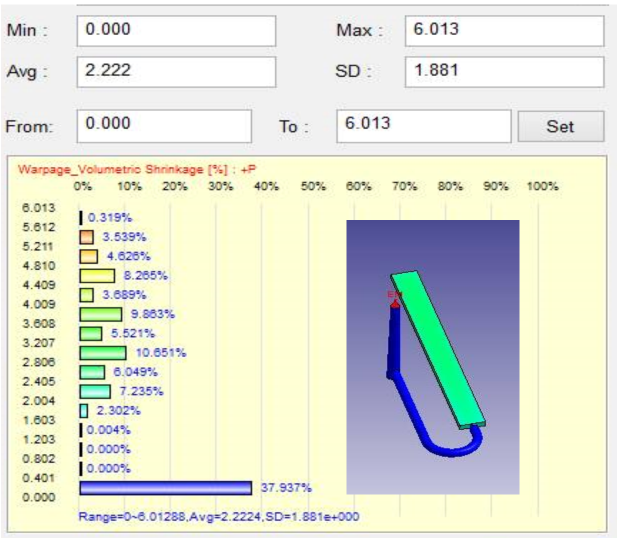


Figure. 3 Measuring of volume shrinkage

Experimental Plan
Factors:7 BaseDesign:7, 16 Resolution: IV

Runs: 64 Replicates:4 Fraction: 1/8
Blocks:1 Center points (total): 0

Design Generators:
E = ABC, F = BCD, G = ACD

Figure. 4 Factional factorial design

4 Classical fractional factorial DOE

For investigating seven factors in a case study process, the fractional factorial design is proposed to identify statistically significant factors. The 2^{7-3} is the specific design providing resolution level IV, which could only focus the significant of the main factors and two-level interactions. However, this design is adequate to be used for the baseline to Taguchi Method and Shainin DOE for a comparative analysis.

4.1 Design of factorial experiment plan

The sixteen different experimental conditions are set with four replicates are performed in each condition and the volume shrinkage (%) is measured as an experimental response. According to the experimental plan, 64 response values would be the results. Fig. 4 presents characteristic of experimental plan for the 2^{7-3} fractional factorial design.

4.2 Experiment result and ANOVA analysis

After 64 experiments are carried out aligned with factorial design concept, ANOVA is used to evaluate significant factors based on statistical principle. The statistic software is used to calculate and construct the ANOVA table as illustrated in Fig. 5. It shows that the three main factors and three interactions are significant to volume shrinkage at confident level of 0.95 (α=0.05). Such the statistically significant factors are Melting temperature (B), Packing time (E) and Cooling time (G), while the significant interactions are BE, BG, and EG.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P
Model	6	222.394	37.0657	51.67	0.000
Linear	3	206.957	68.9858	96.16	0.000
B	1	26.668	26.6682	37.17	0.000
E	1	85.556	85.5556	119.26	0.000
G	1	94.734	94.7337	132.05	0.000
2-Way	3	15.436	5.1455	7.17	0.000
B*E	1	3.433	3.4331	4.79	0.033
B*G	1	3.611	3.6114	5.03	0.029
E*G	1	8.392	8.3919	11.70	0.001
Error	57	40.893	0.7174		
Lack-of-Fit	9	3.627	0.4030	0.52	0.854
Pure Error	48	37.266	0.7764		
Total	63	263.286			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.847002	84.47%	82.83%	80.42%

Figure. 5 ANOVA table of fractional factorial design

4.3 Setting of optimal condition

The key response is volume shrinkage as the quality characteristic of plastic work-piece, which the less percentage of volume shrinkage, the better quality of injection molding process. Liner equation constructed from experimental data in this methodology is shown in Eq. (2), where Y_1 is the percentage of volume shrinkage. The optimum condition can be considered from relation of the equation including interaction and main effect plots as shown in Fig. 6.

$$Y_1 = 9.129 + 0.646\,B - 1.156\,E - 1.217\,G - 0.232\,BE - 0.238\,BG + 0.362\,EG \quad (2)$$

The optimal condition is Melting temperature (B) of 215'C, Packing time (E) of 6 seconds, and Cooling time (G) of 14 seconds. By using the equation developed from this 2^{7-3} design, the lowest estimation of volume shrinkage in percentage is 6.94%.

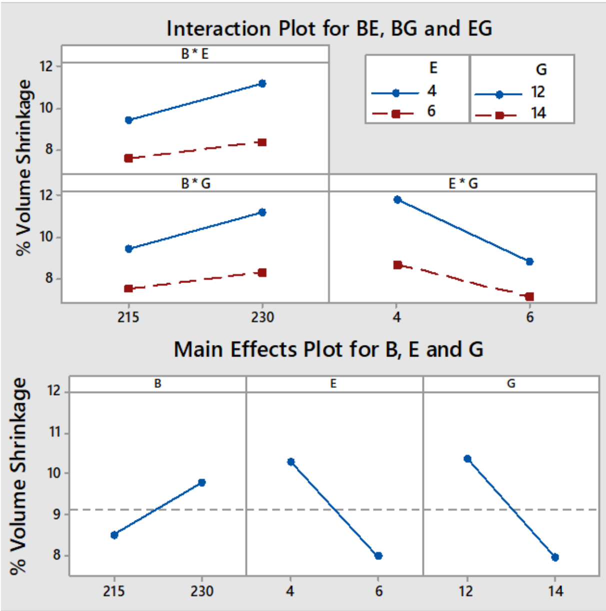


Figure. 6 Main effect and interaction plots

Table 2. Taguchi experimental plan and results

No.	A	B	C	D	E	F	G	Volume Shrinkage (%) (four replicates)
1	-	-	-	-	-	-	-	12.146, 12.142, 10.652, 10.652
2	-	-	-	+	-	+	+	08.528, 09.092, 07.540, 07.540
3	-	-	+	-	+	-	+	07.769, 07.769, 06.192, 06.192
4	-	-	+	+	+	+	-	09.093, 09.093, 07.541, 07.541
5	-	+	-	-	+	-	-	10.213, 10.213, 08.683, 08.683
6	-	+	-	+	+	+	+	08.436, 08.436, 06.872, 06.872
7	-	+	+	-	-	-	+	10.135, 10.135, 08.602, 08.602
8	-	+	+	+	-	+	-	14.837, 14.649, 13.199, 13.199
9	+	-	-	-	+	-	+	07.545, 07.545, 05.964, 05.964
10	+	-	-	+	+	+	-	08.924, 08.924, 07.369, 07.369
11	+	-	+	-	-	-	-	11.072, 11.072, 09.557, 09.557
12	+	-	+	+	-	+	+	08.900, 08.900, 07.344, 07.344
13	+	+	-	-	-	-	+	09.862, 09.862, 08.324, 08.342
14	+	+	-	+	-	+	-	13.170, 13170, 11.695, 11.695
15	+	+	+	-	+	-	-	10.105, 10.105, 08.591, 08.591
16	+	+	+	+	+	+	+	08.031, 08.031, 06.459, 06.459

5 Taguchi method

5.1 Experiment plan of Taguchi method

In this methodology, the experimentation has been done in the previous work of authors [8]. The Orthogonal Arrays (L16) are used to study the seven factors and theirs interaction, resulting in sixteen different experimental conditions are set as shown in Table 2. Four replicates were performed in each condition and the percentage of volume shrinkage is measured as responses. The overall experiments are run on 64 experiments similar to those of 2^{7-3} design.

Analysis of Variance for Means

Source	DF	Seq SS	Adj SS	Adj MS	F	P
B	1	6.697	6.697	6.6967	20.39	0.001
E	1	22.519	22.519	22.5192	68.58	0.000
G	1	24.959	24.959	24.9595	76.01	0.000
E*G	1	2.834	2.834	2.8344	8.63	0.013
R.Err.	11	3.612	3.612	0.3284		
Total	15	60.622				

Figure. 7 ANOVA table of Taguchi method

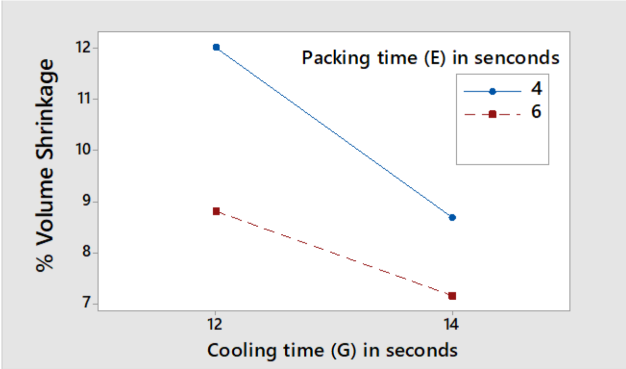


Figure. 8 Interaction plot of Taguchi method

5.2 ANOVA table and analysis

The ANOVA test, a statistical technique, is used to identify significant factors affecting the response. The results are shown in Fig. 7. The confidential level for testing is set at 95% (α 0.05) and the p-valve below 0.05 is statistically significant.

The four significant factors to Volume shrinkage are Melt temperature (B), packing Time (E), Cooling time (G) and interaction of E and G (EG).

5.3 Prediction of optimal level and performance

Due to orthogonal array design, the linear equation to express relation between statistically significant factors to response can be derived. The Eq. (3) provides the Volume shrinkage (Y_1) in function of Melt temperature (B), Packing time (E), Cooling time (G) and Interaction of EG. The lowest prediction of %volume shrinkage is 6.51%, obtaining from 215'C of melting temperature, 6 seconds of packing time and 14 seconds of cooling time. The interaction plot of EG is also presented in Fig. 8 to illustrate the optimal setting of injection molding process.

$$Y_1 = 9.1731 + 0.6470\,B - 1.1864\,E - 1.2490\,G + 0.4209\,EG \quad (3)$$

Where, Y_1 is % of Volume shrinkage

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Table 3. Identify factors and their levels

Parameters	Level		Units
	Low (-) Marginal Level	High (+) Best Level	
1. Filling time (A)	2	3	sec.
2. Melt temperature (B)	230	215	°C
3. Mold temperature)C)	60	35	°C
4. Maximum injection pressure profile value (D)	50	80	%
5. Packing time (E)	4	6	sec.
6. Maximum packing pressure profile value (F)	30	50	%
7. Cooling time (G)	12	14	sec.
Response value 1	14.661	5.964	%
Response value 2	14.649	7.545	%
Response value 3	13.199	5.964	%

6 Shainin DOE

The Shainin DOE is applied in four simple steps to identify the most three factors affecting volume shrinkage, which are called Red X, Pink X and PalePink X from the most to less important.

Step1: Identifying input factors and decision limits

The Best Level and the Marginal Level after conduct three replicate experiments as shown in Table 3.

Accordingly to the experiment, results of All-Best are better than those of All-Marginal. The median of All-Best is 5.964, while median of All-Marginal is 14.649, thus D = 14.649-5.964 = 8.685, and $\bar{d}$ = ((7.545-5.964) + (14.661-13.199))/2 = 1.521, so D : $\bar{d}$ = 8.685 : 1.521 or 5.71 : 1 which is greater than 1.25 This indicates that at least one of the selected factors (A to G) is significant.

Step 2 : Separating important and unimportant factors

The range of the decision limits (high side) is = 5.964 + 2.776 $\bar{d}$ /1.81 = 3.630 to 8.298 and decision limits (low sides) = 14.649 + 2.776 $\bar{d}$ / 1.81 = 12.315 to 16.983. The tests of significant are performed by comparing the response results of each factor to the decision limits. From the experimental results in Table 2, it shows that the responses of factor E and G are out of the decision limits therefore factor E and G are significant factors.

Step 3 : Confirming of important factors

From the experimental results, $E_BG_BR_M$ and $E_MG_MR_B$ fall within the decision limits so factors E is interaction with G. Therefore, factors E, G and EG interaction are significant as the results shown in Table 5.

Table 4. Separation of important and unimportant factors

Test	Combi-nation	Result	Median	Decision Limits	Conclu-sion
1	A_MR_B	7.745	5.964	3.630 to 8.298	A not Sig.
2	A_BR_M	13.498	14.649	12.315to 16.983	
3	B_MR_B	6.461	5.964	3.630 to 8.298	B not Sig.
4	B_BR_M	12.341	14.649	12.315to 16.983	
5	C_MR_B	7.544	5.964	3.630 to 8.298	C not Sig.
6	C_BR_M	14.645	14.649	12.315to 16.983	
7	D_MR_B	5.946	5.964	3.630 to 8.298	D not Sig.
8	D_BR_M	13.199	14.649	12.315 to 16.983	
9	E_MR_B	8.728	5.964	3.630 to 8.298	E Sig.
10	E_BR_M	8.971	14.649	12.315 to 16.983	
11	F_MR_B	7.593	5.964	3.630 to 8.298	F not Sig.
12	F_BR_M	14.182	14.649	12.315 to 16.983	
13	G_MR_B	8.816	5.964	3.630 to 8.298	G Sig.
14	G_BR_M	8.842	14.649	12.315 to 16.983	

Table 5. Confirmation of factors

Test	Combination	Result	Median	Decision Limits	Conclusion
1	$E_BG_BR_M$	6.816	5.964	3.630 to 8.298	EG significant
2	$E_MG_MR_B$	11.071	14.649	12.315 to 16.983	

Step 4 : Conducting factorial analysis and optimal setting

From factor analysis in Table 6, it can be concluded that factor G (Cooling time) is the most important, Red X, whose effect is equal to 3.397%. The second most important called Pink X is factor E (Packing time) and the result of effect is 3.286%. The third important factor is the interaction between factors E and G (EG), PalePink X, and the result of effect is equal to 1.319%. The interaction plot of EG for % volume shrinkage is demonstrated in Fig. 9.

Table 6. Factor analysis and their effects

	E Best	E Marginal
G Best	7.745 6.816 6.461 5.964 7.544 7.545 5.964 5.964 7.593 Median = 6.816	8.723 8.842 Median = 8.783
G Marginal	8.971 8.816 Median = 8.894	13.498 11.071 12.341 14.661 14.645 14.649 13.199 13.199 14.182 Median = 13.498

↓

E Best = 6.816+8.894 = 15.710	G Best = 6.816+8.783 = 15.599
E Marginal = 8.783+13.498= 22.281	G Marginal = 8.894+13.498= 22.392
$E_B G_B$-$E_M G_M$ = 6.816+13.498= 20.314	$E_M G_B$-$E_B G_M$ = 8.783+8.894 = 17.677

Main Effect E = |(15.710-22.281)| / 2 = 3.286
Main Effect G = |(15.599-22.392)| / 2 = 3.397
EG Effect = |(20.314-17.667)| / 2 = 1.319

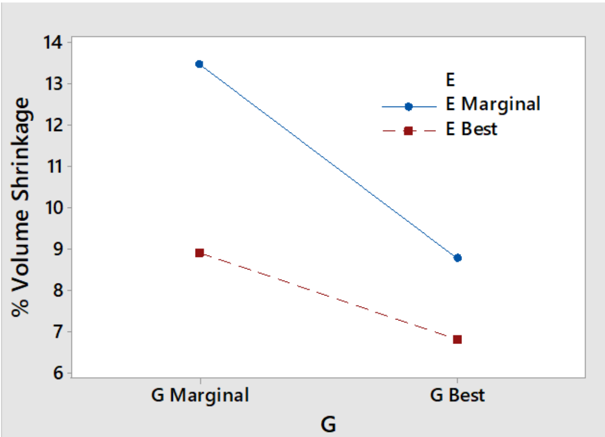

Figure. 9 Interaction plots of EG

The optimal condition can be set at high level of Packing time (E) and Cooling time (G), which are 6 and 14 seconds, respectively. In Shainin DOE, the setting can yield the lowest volume shrinkage of 5.96 %.

7 Comparison of three DOE approaches

Applications of Taguchi and Shainin DOE are compared to the classical fractional factorial, 2^{7-3} design. It has been possible to comparatively analyze both the ease of implementation and the accuracy of result concluded from those methodologies. Based on a case of plastic injection

Table 7. Significant factors of DOEs

DOE Type	Significant Factors						Linear Model
	B	E	G	BE	BG	EG	
2^{7-3} Fractional Factorial	√	√	√	√	√	√	√
Taguchi Method	√	√	√			√	√
Shainin DOE		√	√			√	

molding process, seven factors are investigated for influencing to the volume shrinkage as a key quality characteristic of work-piece produced. Some essential issues can be addressed as follows.

- All significant factors among three DOE approaches are presented in Table 7. Fraction factorial design can detect the most number of factors based on ANOVA technique which is a principle analysis tool and also is used in Taguchi Method. However, when the most three important factors are highlighted, the results of all DOE approaches are the same, (E, G, and EG). This indicates that both Taguchi and Shainin DOE can provide the correctness of analysis relative to the classical 2^{7-3} design. It should be noted that the basic of Shainin DOE is to determine only the most three factors causing variations, which can mostly practical solve the quality problem in field work.
- The optimal conditions of significant factors are found at Melting temp (B) at low level including Packing time (E) and Cooling time (G) at high level. All DOE approaches also provide the same results of optimal condition, but the prediction values of lowest volume shrinkage are different based on their different experimental data. Shainin DOE gives the lowest % volume shrinkage at 5.96%, while 2^{7-3} and Taguchi method yield at 6.94% and 6.51%, respectively. However, there is an advantage of 2^{7-3}design and Taguchi method over Shainin DOE by providing the linear equations to estimate volume shrinkage, which enhances a mean to further optimize process performance.
- It is claimed that Shainin DOE tools are very effective in manufacturing industries to solve the problem of process optimization. Within the world of Design of Experiments, the Shainin DOE provides the simplest, easiest and most effective ways to get the solution [17]. In this exploration, the Shainin DOE used the less number of runs to perform the test comparing to both 2^{7-3} design and Taguchi method. All detail

Table 8. Comparison of DOE approaches

Characteristic	DOE Approaches		
	2^{7-3} design	Taguchi Method	Shainin DOE
Number of Test	64 runs	64 runs	22 runs
Cost of Experiment	High	High	Low
Analysis Tools	ANOVA	ANOVA, Orthogonal Array	Median, Interaction Plot
Complexity	Moderate	High	Low
Ease of Implement	Difficult	Difficult	Easy

comparative perspectives are summarized in Table 8. The ease of implementation of Shainin DOE is also an advantage over another two DOE approaches. However, its weakness is in the skill and knowledge required to firstly correctly identify the factors and then secondly, to allocate levels of factors to the experimental condition. This relies on pre-experimental analysis or substantial knowledge of a case study.

8 Conclusion

A comparative analysis of application of three DOE approaches, (Fractional factorial design or 2^{7-3} design, Taguchi method and Shainin DOE) is investigated in this work. A case of common process found in industrial environment is the subject of the application, in which process parameters of injection plastic molding as factors and the volume shrinkage of work piece as a key response. The general conclusion from the experiments can be drawn.

The outcomes of significant factors are slightly different, but the top three significant factors obtained from three DOE approaches are the same. This proves that the accuracy of Taguchi and Shainin DOE is similar to that of 2^{7-3} design.

In order to find out the optimal condition in the plastic injection molding process, the result of suitable setting from these three DOEs are also the in the same optimal condition. Shainin DOE provides the lowest prediction of % volume shrinkage at 5.96%, while 2^{7-3} and Taguchi method yield the volume shrinkage of 6.94% and 6.51%, respectively.

Although the significant factors and optimal conditions found in this work are alike, the way to implement each DOE approach is different. Shainin DOE is usually considered as a simply method with the less number of experiments, which is the one of practical alternative in applying to industry. Factorial design and Taguchi method is more complex in term of using high statistical analysis and need a lot of experiments to confident the conclusion. Moreover, this study supports the need to explore and compare thoroughly the concepts and significance of DOE approaches as well as analyze and find out the applicability of Taguchi and Shainin DOE in industrial processes.

For further study, although the credibility of the DOE methodology itself, together with the case illustration, promotes its generalization for application, these DOE approaches need to be tested in a process with more factors involved to be studied comparatively in term of the accuracy of information and the ease of implementation to elaborate their effectiveness and advantage in a more complex experiment.

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