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Development of Training Kit for Learning Taguchi Method and Design of Experiments

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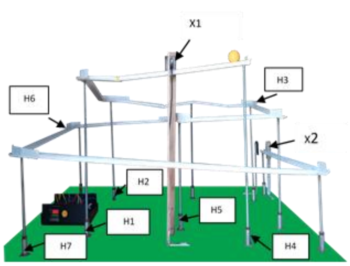
Graphical abstract



Abstract

This study focused on designing a training kit for learning design of experiment (DoE). A model has been established to provide a platform and facilities to conduct design of experiment. A system of ball rolling on a designated track has been made to fulfill this objective. Several factors could be set up to conduct real experiments repetitively. To verify the feasibility of this training kit, four different kind of experiments have been used to test the reliability of the factors levels and their response quality characteristics. Taguchi L8 and L9 matrices are used to find the optimum response time for a ball to complete the full travelling cycle, with quality objective of smaller the better, the conducted experiments achieved some results between Taguchi and Factorial designs that were used to confirm the experiments. The corresponded travelling time for Taguchi experiment and experimental solution of 24 factorial designs are 11.25 s and 11.43 s respectively, both falls within 90% confidence interval.

Keywords: Training kit; feasibility; factorial design; Taguchi method

Abstrak

Kajian ini memfokuskan dalam mereka bentuk kit latihan untuk mempelajari reka bentuk eksperimen (DoE). Satu model telah dibangunkan bagi membina platform dan kemudahan untuk menjalankan reka bentuk eksperimen. Satu sistem bola yang bergolek di atas trek yang ditetapkan telah dibuat untuk mencapai objektif ini. Beberapa faktor boleh dibangunkan untuk menjalankan eksperimen sebenar berulang kali. Untuk mengesahkan daya maju kit latihan ini, empat jenis eksperimen yang berbeza telah digunakan untuk menguji kebolehpercayaan tahap faktor-faktor dan maklum balas ciri-ciri kualiti yang diberikan. Matriks Taguchi L8 dan L9 digunakan untuk mengkaji masa tindak balas yang optimum bagi bola tersebut melengkapkan sepenuhnya perjalanan kitaran, dengan objektif kualiti lebih kecil lebih baik, eksperimen yang dilakukan telah menghasilkan keputusan bagi Taguchi dan faktoran reka bentuk yang telah digunakan untuk pengesahan eksperimen. Nilai masa perjalanan bola bagi eksperimen Taguchi dan penyelesaian eksperimen rekabentuk faktoran 24 adalah masing-masing 11.25 s dan 11.43 s, kedua-duanya jatuh dalam selang keyakinan 90%.

Kata kunci: Kit latihan; daya maju; reka bentuk faktoran; kaedah Taguchi.

1.0 INTRODUCTION

Learning design of experiment for practical and actual application is the crucial part of any preparation of design or process optimization. The ability to perceive and evaluate result of any experiment is important to unfold the content of design analysis and the depth exploration of any process and system. Since there are various kinds of design experiment types and approaches, effective and user friendly tools will attract practitioners and affects its wide and extensive application of design of experiment.

The applications of DoE were then noted for several key criteria such as for research and design, product and process optimization, screening and problem solving. Hence, product and process optimization is the main criteria where DoE is highly used for improving such level of quality performance. In the case of Taguchi Method, it is very important to understand noise factors before conducting an experiment, Taguchi method emphasizes this to be explored and known. Noise will affect the accuracy of results obtained from any experiment, insensitivity of design intents is affected by variability transmitted from noise factors and they can cause reduction in design robustness and reliability during system life cycle. The approach confined its scope of experiment within a possible controlled situation after knowing the noise factors. In optimization of products or processes, improvement are expected to be achieved when results produce better quality performance; reduce processing cost, increase output quantity and sustain desired product performance. Typical example in machining process, the optimization is assessed by productivity, total manufacturing cost and other relevant criteria [1]. Taguchi method is leading the application area in the optimization of product and process designs, it has been reported that Taguchi method has simplified the analyzing method and reduce the experimental time and as a result, cost saving could be achieved by optimizing many quality characteristics with very few numbers of experiments [2].

Significantly, many Taguchi successful experiments have improved a lot of industrial works, designs and processes [3]. Taguchi method focuses on experiment conducted without interaction analysis of factors in its responsive effect, this is apparent when noise factors are known and experiment is run under controlled. Noise factors are run or tested as replications [4]. The robustness of the experiment in product or process design has created insensitiveness to uncontrollable environmental condition [5]. To compare the effectiveness, two experiments were conducted for same factors and response variable to compare the results between the result from Taguchi method and central composite design are found to be similar [1]. Next significant use and application of Taguchi method is in multi-response variables which is much more complicated than optimization of single quality characteristic [6]. Knowledge and experiences of relevant engineering subjects are required to decide optimum decision making in relation to cost, productivity and performance when response variables are interconnected with each other. In design of experiments, factors are chosen because they displayed great degree of uncertainty and variability to output responses [7].

The steps in conducting the Taguchi method are explained in sequence from recognition of problem until conduct of a confirmatory experiment [8]. Verification of the optimum setting obtained from the result of experiment is the vital step to confirm the Taguchi experiment is accurate and reliable for next decision making. Results of the confirmatory test shall be within plus minus 90% to 99% confidence interval, as suggested by practitioner, Ranjit Roy [9]. Since design of experiments are widely used not only for optimization purpose, such application are in research, developing control variables and understanding attributes factors and its phenomenon. In industry, factorial designs are widely used in experiments [10]. However there are many occasions in experiments that interaction effects are of the interest in the study. These concerns are influenced by the degree of criticality of the responses and the sensitivity of the factors effects which was scientifically determined from past records. An option to this, factorial design of experiments are commonly used to explore and screen a large number of potential factors effect, how far it could affect changes to the output response are possible to be studied. It is common that key factors and noise factors are experimented together using fractional factorial in combined arrays in screening experiment [11]. As the objective of an experiment is to determine the effect of factors to subject under study, factorial approach has its own diversified methodology from step to step to higher order of the design of experiments. The design has complimentary approach to consider every single factor to be analyzed, from lower order resolution to higher order, from factorial to star point of design cube and from selective range to computed selection of testing range. However it was found that higher order interaction in fractional factorial design was assumed insignificant in comparison with the main effect and as a result, relatively clear main effects will be obtained from the experiment [7]. The most economical factorial design in screening experiment is the fractional factorial of resolution III, an experiment conducted with no interaction study [12]. Resolution IV of factorial designs is used extensively in screening experiment [13]. Further analysis for significant and selected factors are enhanced through the application of more detail design, for example, for non-linear- responses, central composite design approach are highly recommended [12]. Alternatively, full factorial with few number of determined factors are often used to analyze their effects and the optimum result. In addition, response surface method is used to develop regression model to predict desirable output with optimum parameters setting.

Some important points to an experimenter are the intentions to conduct experiments, followed by selection of the appropriate type of these experiments to suit their objectives. These could only be achieved with profound understanding on how experiment is configured, planned, executed and visually being employed in analyzing factor effects. As experiment shall be planned for obtaining appropriate data for statistical analysis, this is important to attain valid and objective conclusion [1]. Nevertheless, when using DoE as improvement tools such awareness of potential issues that could arise during the journey shall be highly considered, prior knowledge of any possible problem will prevent wrongdoing and abandoned of the great effort [14]. Therefore, the studied in design of experiment requires repeated observations and experiences. This quality is expected to be acquired prior to positioning in the work place, research and improvement activities.

There are many design of experiments conducted in regards to academic researches as well as huge application in industrial environment, nevertheless less are focusing on developing the skills, fundamental ability and practical usages of the design of experiment [15]. As reported, the basic problem in experimental designs, are the establishment of appropriate and reliable design criteria followed by selection of the corresponding designs [16]. There is no established standard to verify the competency of learner on its ability to perform the DoE. This has indicated that knowing the right DoE and its application is still not a major concerned in several organization and institution. There are several kits and software that could assist these short-comings but it was not focused on teaching for fundamental in real applications. Such details information is expensive to be obtained by a beginner. Furthermore, there are many learning package developed and intended for commercial purpose, and where it is permissible for reference, some limitations are imposed, typically for the trial version. At the end, cost factor has become the main reason to upbringing the learning curve. This phenomenon need to be resolved if the ability of the young learners, engineers, anyone who is designated with the tasks, beginners and early researchers are expected to have minimum capability to do the design of experiment in their respective field. For instance, by realistic numerical contribution, engineers can estimate the magnitude and direction of the effect of factors [17]. In a research, repetitive, practice and rehearsal are important to acquire level of competency and to become proficiency in any particular area [18].Therefore, conducive and repetitive learning in design of experiment is necessary to support the learning to be more effectives. Effectives learning will trigger creativity in further applications. The success to the effective learning could be complemented by establishing a standard for assessing the capability or competency of any learner.

2.0 METHODOLOGY

In order to have repetitive experiment, it requires components of the operating system to be driven by a consistent energy. As the effect of gravitational force is always similar to the center point of gravity, this is found in the simple dynamic system of ball rolls on track, where a sphere moving on a plane at certain angle is due to the gravitational force applied to the mass of the rolling ball. In this system the potential energy is assumed the same as the kinetic energy which is transformed in the movement of rolling sphere over an angle of a plane. The friction force is considered zero as railing system is applied therefore only heights that produce angle at each plane are contributing to speed and time travelling over the distance. The travelling time could be obtained repeatedly while heights of the planes are adjusted to vary the effect on the ball's speed as per experimental combination setting. There is no additional cost and new materials to run and repeat each experiment, the same sphere ball and columns are used to perform the series of test.

The evaluation in this experiment is made on the observation of a ball rolling on a designated path at several heights of gravitational effect. The learning kits are developed similarly to system of roller coaster, using thin sphere ball rolling from the heights determined at certain angles. The ball is released at a point where kinetic energy is applied; the starting point which is pre-determined is spotted by a first proximity sensor linked to an electronics timer. The ball will roll along the designated path of rail with support at several points. The height of each support is set based on the purpose of study. At the end of each cycle, a proximity sensor is installed to detect the final contact of travelling time. The objective of this study is to evaluate the feasibility of the training kit in repetitive learning of design of experiment (DoE). The quality characteristic set for the experiment is the smaller the better, to obtain the smallest travelling time in second (s) within the selected ranges of each factor levels. Other quality characteristics such as nominal the best and bigger the better are testable with the same operating system of the designed kit. This target is set for both Taguchi and factorial design of experiments. Prior to optimization of factor levels, screening experiments will be conducted to identify significant factors. This input will be used in Taguchi and Factorial optimization experiments. Figure 1 is showing the complete system for the experimental testing.

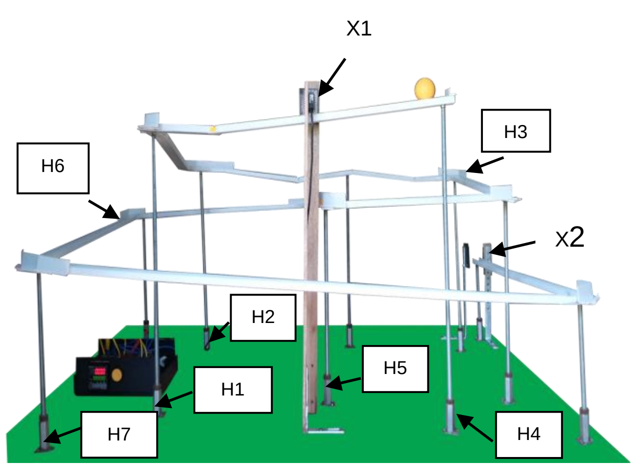


Figure 1 Complete ball and track system applied in the experimental kits

There are seven factors selected to be experimented with one single response variable as detailed in Table 1. The response variable is the time taken for the ball to travel from point X1 to point X2. Table 1 depicted the factors and their levels set for the experiments. Such factors are determined in a manner that the ball will be able to roll from one level to another level to complete the whole cycle. Predetermined or test is required to confirm this setting applicability. The ball weight is 2 grams and is set as a constant factor.

Table 1 Factors and levels of experiment

Factor	Level 1	Level 2	Scale unit
1- Height 1	47	50	cm
2- Height 2	44	47	cm
3- Height 3	40	43	cm
4- Height 4	38	40	cm
5- Height 5	35	38	cm
6- Height 6	32	35	cm
7- Height 7	28	31	cm

Two types of design of experiments are selected for this case study; Taguchi method and fractional factorial design. The first experiment will be the Taguchi method. It will be conducted in matrix of L8. The P diagram for this 1st stage of L8 experiment is shown in Figure 2. The second method will be the fractional factorial. The reason being to use this fractional factorial is its reduction in number of experiments and its similarity to the Taguchi method.

As known, fractional factorial is tightly connected with the notion of orthogonal arrays [11]. In order to justify the effectiveness of the designed kit in teaching the DoE, comparison analysis of the two different types of experiments will be conducted. Fractional factorial 2^{7-3} experimental matrix is used in this first stage screening experiment. The Taguchi method of experiment is conducted based on the designed excel templates with reference to Taguchi techniques employed and written by several experts [19]. The fractional factorial and full factorial are conducted based on trial version of the Design Expert 8 software.

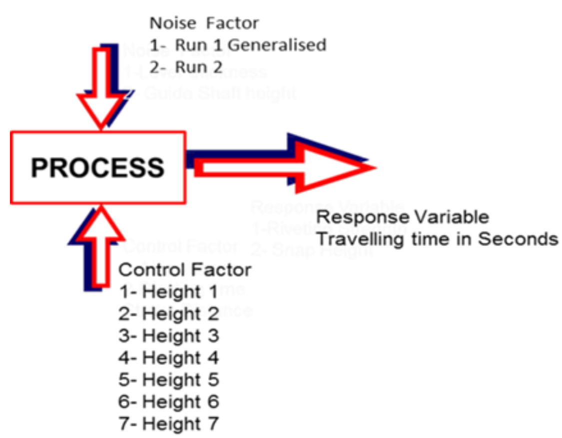


Figure 2 The P diagram for 1st stage of L8 experiment

The L9 matrix is used to determine the optimum condition and factors setting. The levels are set within the range of previous L8 experiment setting. From the L9 the magnitude of factor effect is plotted to determine the optimum setting, this will be confirmed by the ANOVA. Four repetitive readings are taken for each run to represent the possible noise factors. And the output is finally calculated in the form of S/N ratio. Figure 3 is the P diagram for the 2nd stage of L9 experiment. Full factorial of 2^4 will be conducted as a comparison experiment.

Information obtained from the screening experiments will be an input to decide number of factor used for the second stage of optimization experiment. Results from full factorial experiment will be compared with the result obtained from the Taguchi L9 experiment. All experiments are run in a confined room to avoid significant wind or air resistance effects. There are two criteria that will be tested for comparison: level of the significant of each factor and the optimum setting for the expected output performance. The magnitude, significant of each factor effect and the optimum parameter setting for the same desired objectives suggested by each different type of the design of experiments will be evaluated and analyzed.

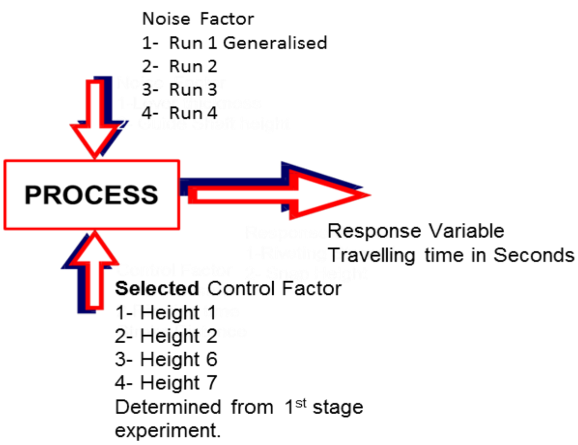


Figure 3 The P diagram for 2nd stage of L9 experiment.

3.0 RESULTS AND DISCUSSION

Result of L8 is recorded in Table 2, it has revealed four significant factors that are influencing the travelling time. Figure 4 of the main effect graph of S/N ratio has shown that, Factor H1, H2, H6 and H7 are significant to affect the travelling time. The main effect graph for each factor is shown Figure 4. H6 is major contributor followed by H1.

Table 2 Result of L8 experiment in S/N ratio

	FACTORS							NOISE FACTORS		
RUN	H1	H2	H3	H4	H5	H6	H7	R1	R2	SN ratio (smaller the better) N
1	47	44	40	38	35	32	28	11.16	11.24	-20.98
2	47	44	40	40	38	35	31	12.01	12.18	-21.65
3	47	47	43	38	35	35	31	11.37	11.80	-21.28
4	47	47	43	40	38	32	28	10.79	10.89	-20.70
5	50	44	43	38	38	32	31	11.78	11.71	-21.40
6	50	44	43	40	35	35	28	11.79	11.87	-21.46
7	50	47	40	38	38	35	28	11.96	12.24	-21.66
8	50	47	40	40	35	32	31	11.48	11.37	-21.16

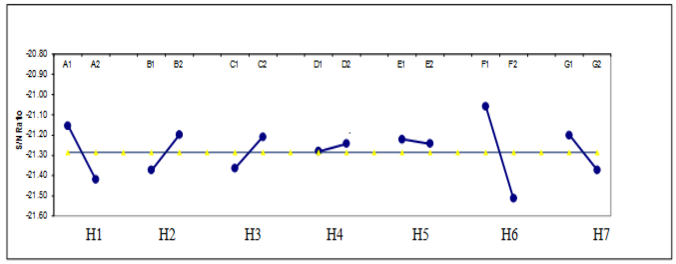


Figure 4 The main effects graph for S/N ratio of L8.

The ANOVA result from Table 3 has confirmed the finding from the main effect graph. H6 is major contributor followed by H1, H2 and H7 respectively. Factor H4 is pooled since the contribution is less than 1%. This provides values of the mean square ratio for each remaining factor. Result of the experiment from Fractional Factorial is shown in Table 4.

Table 3 ANOVA contribution of factor effects for L8 experiment

RUN	Factor/Source	Degree of Freedom	Sum of Squares	Mean Squares	Mean Square Ratio – F	Percent Contribution %
1	Height-H1	1	0.069	0.07	0.178	9.0793
2	Height-H2	1	0.031	0.03	0.079	4.0082
3	Height-H3	1	0.024	0.02	0.060	3.0772
4	Height-H4		Pooled	----	---	--
5	Height-H5	1	0.017	0.02	0.044	2.2598
6	Height-H6	1	0.204	0.20	0.524	26.7513
7	Height-H7	1	0.029	0.03	0.075	3.8378
	Error	1	0.39	0.389		50.99
	Total	7	0.76			100
	Effective DOF Factors	6				

Table 4 Result for fractional factorial experiment 2^{7-3}

		FACTORS							Results
STD	RUN	H1	H2	H3	H4	H5	H6	H7	R1
15	1	47	47	43	40	35	35	28	11.26
4	2	50	47	40	38	35	35	31	11.88
12	3	50	47	40	40	35	32	28	11.19
7	4	47	47	43	38	35	32	31	11.14
16	5	50	47	43	40	38	35	31	11.39
6	6	50	47	43	38	35	35	28	11.98
2	7	50	44	40	38	38	32	31	11.87
1	8	47	44	40	38	35	32	28	11.26
13	9	47	44	43	40	38	32	31	11.98
11	10	47	47	40	40	38	32	28	11.15
8	11	50	47	43	38	38	32	28	11.26
3	12	47	47	40	38	38	35	28	11.49
9	13	47	44	40	40	35	35	31	11.89
10	14	50	44	40	40	38	35	28	11.68
14	15	50	44	43	40	35	32	31	11.71
5	16	47	44	43	38	38	35	31	12.84
18	17	50	44	40	38	38	32	31	11.80
25	18	47	44	40	40	35	35	31	11.98
32	19	50	47	43	40	38	35	31	11.36
23	20	47	47	43	38	35	32	31	11.37
17	21	47	44	40	38	35	32	28	11.14
19	22	47	47	40	38	38	35	28	11.42
28	23	50	47	40	40	35	32	28	11.40
20	24	50	47	40	38	35	35	31	12.15
24	25	50	47	43	38	38	32	28	11.43
27	26	47	47	40	40	38	32	31	11.51
21	27	47	44	43	38	38	35	31	12.31
30	28	50	44	43	40	35	32	31	11.64
26	29	50	44	40	40	38	35	28	11.66
31	30	47	47	43	40	35	35	28	11.49
22	31	50	44	43	38	35	35	28	12.14
29	32	47	44	43	40	38	32	28	12.17

The ANOVA results from Table 5 has shown that height 2(H2) and Height 6(H6) and height 7(H7) are significant, the significant of height 1(H1) lies under the interaction effects in AE(H1H5) and AD(H1H4). Thus, we consider factor height 1(H1) also a significant factor. Significant level is determined when the probability value is less than 0.05, according to calculation made in Design expert software version 8. Table 6 is showing the comparison result of L8 and fractional factorial of 27-3.

It is noted that both experiment agreed on which factors are significant and this are further tested with Taguchi L9 and full factorial design of 2^4. Four factors are selected for these two experiments; height 6(H6), height 2(H2), height 7(H7) and height 1(H1). Experimental data is reported in Table 7. Data plotted for the main effect has significantly shown H6 is most dominant factor and followed by factor H2. This is shown in Figure 5.

Table 5 ANOVA for fractional factorial 2^{7-3}experiment

Source	Sum of Squares	Df	Mean Square	F - Value	p-value Prob > F	
Block	0.031	1	0.031			
Model	4.28	14	0.31	6.79	0.0002	Significant
A-H1	6.15E-004	1	6.125E-004	0.014	0.9086	
B-H2	1.60	1	1.60	35.61	< 0.0001	
C-H3	0.12	1	0.12	2.78	0.1150	
D-H4	0.13	1	0.13	2.83	0.1117	
E-H5	0.090	1	0.090	2.01	0.1757	
F-H6	0.75	1	0.75	16.68	0.0009	
G-H7	0.29	1	0.29	6.42	0.0221	
AB	0.17	1	0.17	3.74	0.0710	
AD	0.27	1	0.27	6.00	0.0262	
AE	0.78	1	0.78	17.23	0.0008	
AF	0.033	1	0.033	0.72	0.4078	
AG	0.026	1	0.026	0.59	0.4544	
BD	0.018	1	0.018	0.40	0.5354	
ABD	1.25E-003	1	1.25E-003	0.028	0.8697	
Residual	0.72	16	0.045			
Cor Total	5.03	31				

Table 6 Summary of results between L8 and fractional factorial 2^{7-3} for factor effects

Code	Source	Ranking in L8		Ranking in 2^{7-3}		Remarks
H1	Height 1 -A	2	Significant	7	Significant	In interaction of AE &AD
H2	Height 2-B	3	Significant	1	Significant	Agreed
H3	Height 3-C	5		5		
H4	Height 4-D	7		4		
H5	Height 5-E	6		6		
H6	Height 6-F	1	Significant	2	Significant	Agreed
H7	Height 7-G	4	Significant	3	significant	Agreed

Non-significant factors in this experiment were pooled as described in the ANOVA as depicted in Table 8.

The pooled ANOVA has provided absolute main factor effects calculation to determine the optimum experimental output condition. The most significant actor is F6 which contributes 53.52%. Factor H7 and H1 were pooled as they were not significant. However factor H2 is remained since its contribution is moderately high at 11.69% despite the low F value.

Table 7 Result of L9 experiment in S/N ratio

	FACTORS				NOISE FACTORS				
RUN	H6	H2	H7	H1	R1	R2	R2	R2	SN ratio (Smaller the better)
1	32	44	28	47	11.72	11.58	11.61	11.66	-21.32
2	32	46	30	49	11.03	11.31	11.18	11.23	-20.98
3	32	47	31	50	11.54	11.49	11.44	11.66	-21.24
4	34	44	30	50	11.77	11.73	11.63	11.65	-21.36
5	34	46	31	47	11.36	11.50	11.44	11.70	-21.21
6	34	47	28	49	11.16	11.20	11.34	11.24	-21.01
7	35	44	31	49	12.16	12.12	11.90	11.92	-21.60
8	35	46	28	50	11.92	11.59	12.04	12.08	-21.52
9	35	47	30	47	1162	12.04	11.75	11.86	-21.45

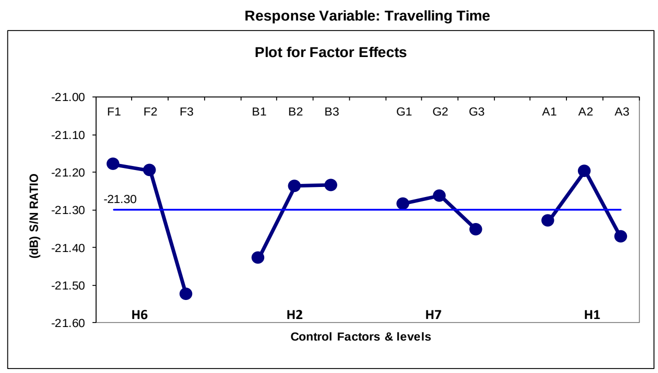


Figure 5 Main effect graph for S/N ratio of L9

Table 8 The pooled ANOVA for Taguchi L9 experiment

RUN	Factor/ Source (Height)	Degree of Freedom	Sum of Squares	Mean Squares	Mean Square Ratio – F	X = not in used or Pooled variance	Pure sum of square	Percent Contribution %
F	H6	2	0.23	0.11	7.15		0.20	53.522
B	H2	2	0.07	0.04	2.34		0.04	11.689
G	H7					X		
A	H1					X		
	Error	4	0.06	0.0159			0.127	34.789
	Total (error)	8	0.37					100.00
	Effective DOF Factors	4						

Below is Equation (1) for calculation of the optimum result in S/N ratio;

$$\text{S/N Optimum} = \text{Mean} + (\text{MH6} - \text{Mean}) + (\text{MH2} - \text{Mean}) \quad (1)$$

The mean of experimental S/N ratio is -21.30 db, MH6 is the highest level of S/N value of the H6(F1) and MH2 is the highest S/N value of the H2(B3).

The Optimum Response in S/N value is therefore calculated as below

Optimum Response = -21.30 db + 0.12 db + 0.07db = 21.11 db

Optimum factor setting is H6 = 32 cm, H2 = 47 cm, H7= 28 cm, H1 = 49 cm. Result of confirmatory run has fallen within the 90% (-20.91 db until -21.31 db) confidence level when its S/N ratio is

-21.03 db and in scale value is 11.25 s. The 90% confidence interval range in scale value is from 11.11 s until 11.63 s. Experiment is validated.

Experiment was continued with full factorial 2^4 and results obtained are shown in Table 9. ANOVA table has revealed the significant level of factor H6 and factor H2 this is correspond to the result obtained from Taguchi L9. The ANOVA table for 2^4 experiments is shown in Table 10. The ANOVA developed in this verification experiment only focus on main effect of the tested factors. As a result the model equation from this experiment is expressed in Equation (2) as below;

$$y = 11.36 - 0.08F + 0.08B - 1.45G - 0.01A \qquad (2)$$

where; y is the estimated optimum response, F is for H6, B is for H2, G is for H7 and A is for H1.

The optimum condition obtained from the experimental solution is 11.43 s with combination of factors at H6 = 35 cm, H2 = 44 cm, H7 = 28 cm and H1 = 47 cm. Even the setting for the full factorial 2^4 experiment are different in levels selection, the objective and quality characteristic value from this optimum setting has fallen within the projected scale value of 90% confidence intervals from L9 experimental result.

Table 9 The result of 2^4 full factorial experiments

STD	RUN	H6	H2	H7	H1	R1
27	1	35	44	31	50	11.27
31	2	35	47	31	50	11.64
15	3	35	47	31	47	11.35
29	4	32	47	31	50	11.52
25	5	32	44	31	50	11.34
23	6	35	47	28	50	11.49
19	7	35	44	28	50	11.44
17	8	32	44	28	50	11.51
3	9	35	44	28	47	11.19
13	10	32	47	31	47	11.86
5	11	32	47	28	47	11.77
1	12	32	44	28	47	11.44
21	13	32	47	28	50	11.87
11	14	35	44	31	47	11.36
9	15	32	44	31	47	11.44
7	16	35	47	28	47	11.54
20	17	35	44	28	50	11.59
16	18	35	47	31	47	12.09
8	19	35	47	28	47	11.88
10	20	32	44	31	47	12.16
32	21	35	47	31	50	11.64
2	22	32	44	28	47	12.08
14	23	32	47	31	47	12.62
26	24	32	44	31	50	11.66
28	25	35	44	31	50	11.99
30	26	32	47	31	50	12.17
22	27	35	47	28	50	12.03
12	28	35	44	31	47	11.58
24	29	35	47	28	50	12.16
6	30	32	47	28	47	11.95
4	31	35	44	28	47	11.69
18	32	32	44	28	50	12.13

Table 10 ANOVA for 2^4 factorial experiment

Source	Sum of Squares	Df	Mean Square	F –Value	p-value Prob > F	
Block	1.71	1	1.71			
Model	0.86	4	0.21	6.11	0.0013	Significant
F-H6	0.42	1	0.42	11.88	0.0019	
B-H2	0.43	1	0.43	12.27	0.0017	
G-H7	1.531E-004	1	1.531E-004	4.369E-003	0.9478	
A-H1	9.453E-003	1	9.453-003	0.27	0.6079	
Residual	0.91	26	0.035			
Cor Total	3.47	31				

4.0 CONCLUSION

Results have shown that Taguchi experiment has been successfully conducted through this training kit and the tested factorial designs in principle agreed with information obtained from Taguchi method. There are however differences in factor level settings and amount of the magnitudes of each factor due to statistical inference made when interaction is considered and used in the calculation of the optimum output. The selection of appropriate factorial design in experimental study requires careful and objectively selected as some interaction effects could not be captured in the optimization process. But this could be overcome by Taguchi method as the actual confirmation result is always matching against the expected confidence levels. The model made for learning design of experiment are proven feasible with easy and fast experimental preparation as well its adequacy to represent a mechanism in understanding between factors and effect. The study could also be done for other type of DoE techniques and the training kit needs further upgrade to reduce several noise factors. The significant outcome of this experimental unit is its ability to provide repeated learning of DoE, learners could repeat the experiment to understand possible errors and how they will affect their experimental results.

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