Teaching Design of Experiment and Response Surface Methodology Using Paper Helicopter Experiment

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***Abstract*— Design of Experiment is one of the powerful tools with great capability in improving experiments performance. DOE is a powerful Quality Engineering tool that can help managers and engineers to identify main variables which affecting the performance. Response Surface Methodology is also used to determine the input combination of factors which maximize or minimize the objective function. There is a cognitive gap between the knowledge of statistics required by engineers due to lack of education and skills. The main goal of this paper is teaching the combination of DOE (one-half fractional factorial) and response surface methodology to optimize the process performance. For simplicity the paper helicopter is selected as a case study which is quite old and has been widely applied by many statisticians for teaching purpose. The experiment was conducted to optimize the paper helicopter flight time. To achieve this aim the one-half fractional factorial and response surface methodology was adopted to investigate the effect of factors and the interactions between them by considering the minimum number of trials.**

I. INTRODUCTION

Design of experiment have been applied by many manufacturers over the last fifteen years for improving process performance, decreasing process variability, enhancing process yield and etc. [1-3]. Investigations has shown that the application of design of experiment methods by engineering in both services and manufacturing industries is limited also when used they are often conducted incorrectly [4]. It is because of that the statistical educations for engineers at university are usually inadequate. There is not also enough communication between the industrial and academics world so it restricts the DOE application in many manufacturing and service industries. Another important issue is lack of skills and expertise needed by engineers to solve the problems. Thus many industrial engineers having conducted the statistical analysis would not know what to do with the results without assistance from statistical consultants in this field [5]. So there is a huge gap between the statistics knowledge needed by engineers in applying DOE as a problem solving technique [6]. The main objective of this paper is teaching the response surface methodology along with design of experiment (one-half fractional factorial) to the industrial engineers.

One of the most well-known experiments among the statisticians and engineers in both industrial parts and the academic is the paper helicopter experiment [7-9]. This paper is going to conduct design of experiment and response surface methodology for paper helicopter experiment to optimize the performance. To achieve this goal one paper helicopter is designed by using A4 size paper. To do this, some simple items such as paper clip, scissors and paper is required. Having made the paper helicopter, the experiment is done to gather the data and then conduct the statistical analysis. Fig.1 depicts a sample of the paper helicopter.

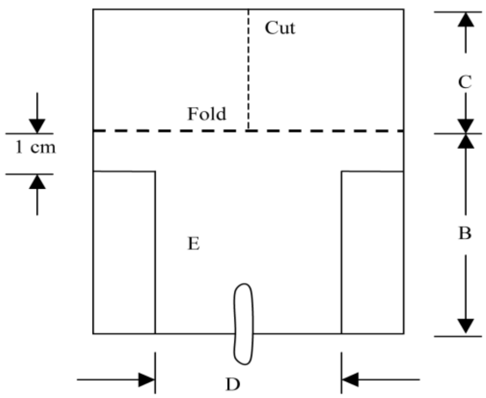

Figure 1. Template for paper helicopter design

DOE is a statistical approach first presented by R.A. Fisher in the 1920's. The goal of his investigation was to analyze the effect of rain, water etc. on the production of crop. He conducted a set of experiments applying orthogonal arrays to restrict the number of experiments [10-11]. Design of experiment (DOE) is a useful approach to determine the best combination of independent variables that maximizes the performance of process. In addition, DOE is an experiment or series of tests conducted by changing the input process variables that may affect the output responses. DOE technique also enables planners to determine the variables that have the most significant effect on the response. In fact, experimental design methods are useful tools for improving the processes. Moreover, DOE provides a full insight of interaction between selected factors that may affect the output results or responses [12].

Response Surface Methodology is an optimization method enabling to identify the input factors combination which maximize or minimize the objective function [13]. RSM is a set of mathematical and statistical approaches which are useful for analysing and modeling of difficulties in which a response of interest is affected by several factors and the objective is optimize the response [14].There are various researchers have evaluated the application of response surface methodology. At first RSM was developed for that goal of determining optimum operating situations in chemical processes by [15]. However it is now applied in different fields and applications not only in engineering and physical, but also in the biological, social and clinical science. In the most RSM problems the polynomial functions widely used for approximating. In other words, the form of relationship between the response and the independent variables is unknown so it is approximated. Initially, a first order polynomial is applied and after that a second order polynomial in the region of the optimum may be used. Next, Popular optimization technique like Gradient method and steepest descent method are applied to detect the optimum of the approximated function [16].

II. RESEARCH METHODOLOTY

A. Design of experiment

DOE includes several steps. First the factors and their levels subject to the experiment should be chosen. After a response variable should be determined to assess the result of experiment. Next, the experiment should be designed and then analysed by using the software.

1. Choosing Factors and Reponse Variable

The factors and levels of paper helicopter experiment have been determined firstly. To perform the experiment 5 factors have been selected. In addition the range of factors have shown in the below table. Table I shows that each factor has two level called high (+) and low (-).

TABLE I. FACTORS AND LEVELS

Factors	High level	Low level
Paper type (A)	70gr	80gr
Paper clip (B)	1	2
Wing length (C)	80mm	100mm
Body length (D)	80mm	100mm
Body width (E)	20mm	30mm

2. Choosing the design for experiment

Having identified the factors and their levels, the proportional design for the experiment should be determined. Due to large number of factors and experiment investigated, the one-half fractional factorial design is used. Fractional factorial design is a fraction of full factorial design. By using the fractional factorial the number of experiments is significantly reduced. To do this method, firstly the resolution of the experiment should be chosen. According to the [12] there are three kinds of design resolution as below:

- Resolution III designs (2^{3-1}_{III}) , I=ABC
- Resolution IV designs (2^{4-1}_{IV}), I=ABCD
- Resolution V designs (2^{5-1}_{V}), I=ABCDE

To perform the one-half fractional factorial one generator (I) is also applied. Every resolution has a specific generator. In this experiment because of one-half factorial design as well as five factors, 2_V^{5-1} design with defining relation I =ABCD is selected.

B. Response surface methodology

1. Steps of Conducting RSM

Three steps are supposed in order to performing the RSM:
1- Phase 0; Brain storming and screening Experiments
2- Phase 1; Process improvement through path of steepest ascent (POSA)
3- Phase 2; Determine optimal condition (Center Composite Design CCD)

Indeed by performing these three phases the best combination and levels for significant factors are determined. At first the mentioned steps are explained briefly as follow:

Phase 0: through this phase the fractional factorial experiment is done as well as the significant factors are identified to perform the RSM.

Phase 1: The experiment will run again base on the significant factors which found in the last phase. So by doing this experiment the number of center point is selected to assess that the response does have any curvature or not?! After running the experiments a regression model or first order model for the responses and factors is constructed. To improve the process the path of steepest ascent (POSA) method is considered. To do this the step size for variable ΔX_i and according to that also ΔX_j is chosen then check the responses.

Phase 2: if the response is relatively close to optimum point, the experiment by the new design will done by considering points that was achieved through phase 1. For acquiring the best point in this phase the second-order model is applied [12].

III. RESULTS AND DISCUSSION

A. Conducting fractional factorial design

The experiment is replicated for three times. Table II depicts each factor has two levels. Therefore, a fractional factorial experiment includes 48 experiments. Following that the response variable is determined. For this experiment the flight time of paper helicopter is considered as the response variables. To select of experimental design, because of the large number of experiments investigated, the fractional factorial design is applied. The plus and minus table for contrast constants for the 2_V^{5-1} design is depicted as below:

Table II. RESULT OF EXPERIMENT

The 2_V^{5-1} Design with Defining Relation I=ABCD						
Replicate	**Basic Design**				**E=ABCD**	**Flight Time**
	A	**B**	**C**	**D**		
1	-1	-1	-1	-1	1	2.08
2	1	-1	-1	-1	-1	2.06
3	-1	1	-1	-1	-1	1.26
4	1	1	-1	-1	1	1.84
5	-1	-1	1	-1	-1	2.39
6	1	-1	1	-1	1	2.20
7	-1	1	1	-1	1	1.52
8	1	1	1	-1	-1	2.11
9	-1	-1	-1	1	-1	2.05
10	1	-1	-1	1	1	2.00
11	-1	1	-1	1	1	2.71
12	1	1	-1	1	-1	2.42
13	-1	-1	1	1	1	2.20
14	1	-1	1	1	-1	2.30
15	-1	1	1	1	-1	2.25
16	1	1	1	1	1	3.10
17	-1	-1	-1	-1	1	2.23
18	1	-1	-1	-1	-1	1.90
19	-1	1	-1	-1	-1	1.55
20	1	1	-1	-1	1	2.00
21	-1	-1	1	-1	-1	2.36
22	1	-1	1	-1	1	2.00
23	-1	1	1	-1	1	1.75
24	1	1	1	-1	-1	1.87
25	-1	-1	-1	1	-1	2.02
26	1	-1	-1	1	1	1.80
27	-1	1	-1	1	1	2.06
28	1	1	-1	1	-1	2.55
29	-1	-1	1	1	1	2.35
30	1	-1	1	1	-1	2.43
31	-1	1	1	1	-1	2.35
32	1	1	1	1	1	2.46
33	-1	-1	-1	-1	1	2.26
34	1	-1	-1	-1	-1	1.80
35	-1	1	-1	-1	-1	1.93
36	1	1	-1	-1	1	1.80
37	-1	-1	1	-1	-1	2.37
38	1	-1	1	-1	1	1.80
39	-1	1	1	-1	1	2.00
40	1	1	1	-1	-1	1.86
41	-1	-1	-1	1	-1	2.48
42	1	-1	-1	1	1	2.20
43	-1	1	-1	1	1	2.52
44	1	1	-1	1	-1	2.35
45	-1	-1	1	1	1	2.30
46	1	-1	1	1	-1	2.20
47	-1	1	1	1	-1	2.15
48	1	1	1	1	1	3.00

The Minitab software is used to analyse the responses. The table III shows the result of experiment after running the Minitab.

Table III. ANOVA RESULT

Term	Effect	Coef	SE Coef	T	P
Constant	2.14979	0.02897	74.22	0.000	
A	0.03792	0.01896	0.02897	0.65	0.517
B	-0.01542	-0.00771	0.02897	-0.27	0.792
C	0.14375	0.07188	0.02897	2.48	0.019
D	0.38792	0.19396	0.02897	6.70	0.000
E	0.04708	0.02354	0.02897	0.81	0.422
A*B	0.23792	0.11896	0.02897	4.11	0.000
A*C	0.07375	0.03687	0.02897	1.27	0.212
A*D	0.07625	0.03813	0.02897	1.32	0.197
A*E	-0.02458	-0.01229	0.02897	-0.42	0.674
B*D	0.31458	0.15729	0.02897	5.43	0.000
C*D	0.01708	0.00854	0.02897	0.29	0.770
D*E	0.04875	0.02438	0.02897	0.84	0.406
A*B*D	-0.04542	-0.02271	0.02897	-0.78	0.439
A*C*D	0.12708	0.06354	0.02897	2.19	0.036
A*D*E	-0.01958	-0.00979	0.02897	-0.34	0.738

The normal probability of these effects is shown in the Fig1. The effects which lie along the line are negligible, whereas the significant effects are far from the line. The significant effects that emerge from this analysis are the main effects of D (body length), C (wing length), and AB, BD and ACD interactions.

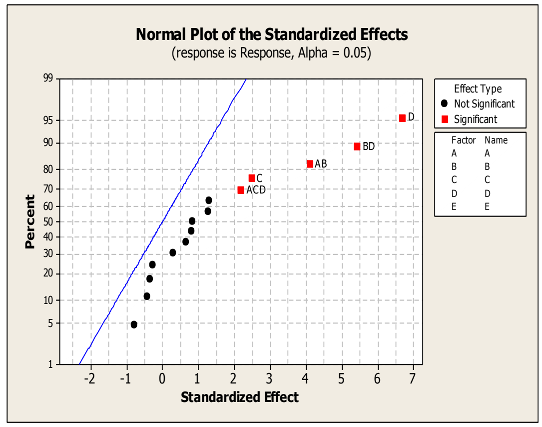

Figure 2**.** Normal probability of effects

The main effects of C and D have plotted in fig.2 and fig.3. The figures illustrate that all of the significant effects are positive, so if we considered only these important factors, we would run all these two factors at the high level to maximize the flight time. However it should be noted that main effects do not have much meaning when they are also involved in significant interactions.

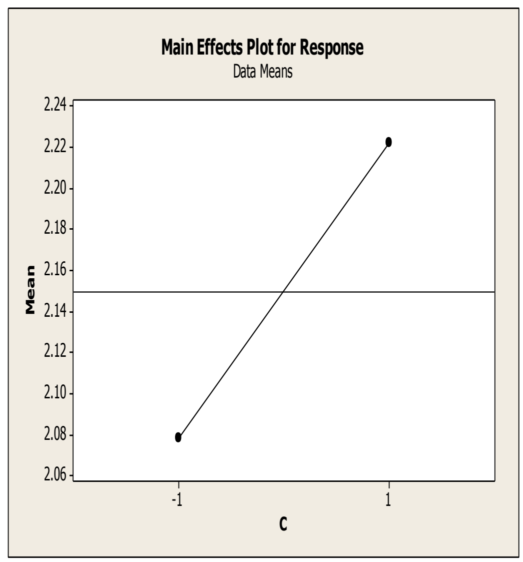

Figure 3. Main effect plot for factor C

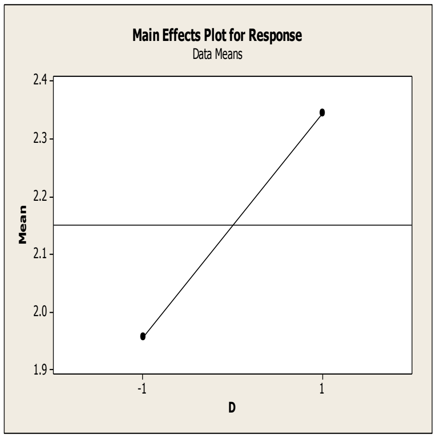

Figure 4. Main effect plot for factor D

Additionally, the AB and BD interactions are plotted in fig.4 and fig.5. Note form the BD interactions that the body length (D) effect is very small when the paper clip (B) is at low level and very large when the paper clip is at the high level, so the best results obtained with high paper clip and high body length. The AB interactions illustrates that paper type (A) has a large negative effect at high paper clip (B) as well as a large positive effect at high paper clip. Therefore the best flight time appear to be acquired when the A, B and D are at high level.

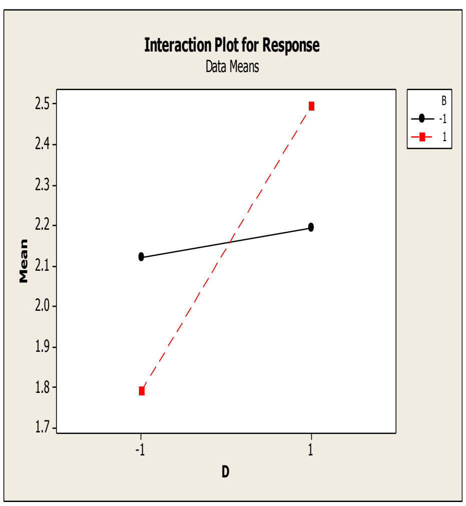

Figure 5. BD interaction plot

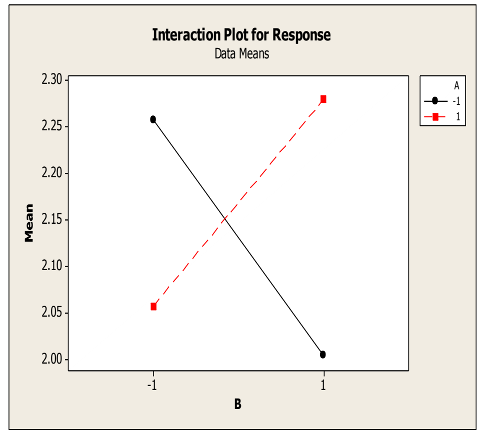

Figure 6. AB interaction plot

1. *Regression model*

Having estimated effects of the significant factors, the following regression model is fitted to the data. Equation.1 indicates the regression model fitted to the data produced by Minitab.

$$Y=B_0+B_1x_1+B_2x_2+B_{12}x_1x_2+\varepsilon \qquad (1)$$

$$Y=2.1497+(0.07188)(x_2)+(0.19396)(x_4)+$$

$$(0.15729)(x_2x_4)+(0.11896)(x_1x_2)+(0.06354)(x_1x_2x_4)$$

According to the result of experiment the factors should be at high level so the value of Y=2.67.

$$Y=2.1497+(0.07188)(+1)+(0.19396)(+1)+$$

$$(0.15729)(+1)(+1)+(0.11896)(+1)(+1)+(0.06354)(+1)(+1)(+1)=2.76$$

2. *Residual Analysis*

The residual analysis is done to validate the regression model. The residual, which are the difference between the observed values and predicted values, should be lie on a straight line in the normal probability plot. Fig.7 and Fig.8 respectively show the normal probability of the residuals and the residual versus the predicted value. Fig.7 shows that residuals lie along a straight line. The residuals are considered to be normal and therefore the validity of the model is investigated. Fig.8 illustrates the plot of residuals versus the predicted response for the model. According to the Fig.8 there is no obvious pattern and it is structure less. So it infers that the suggested model is adequate.

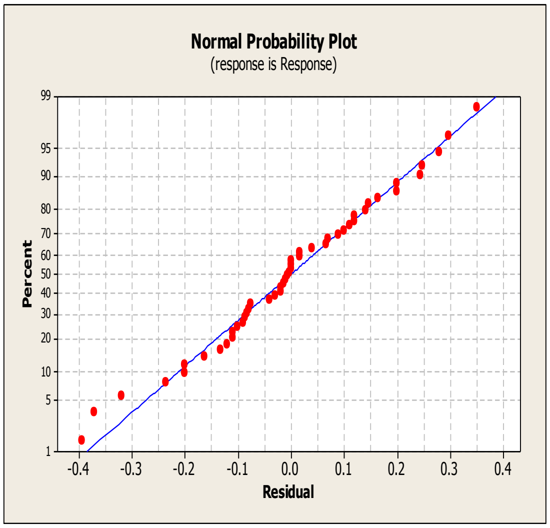

Figure 7. Normal probability plot of residuals

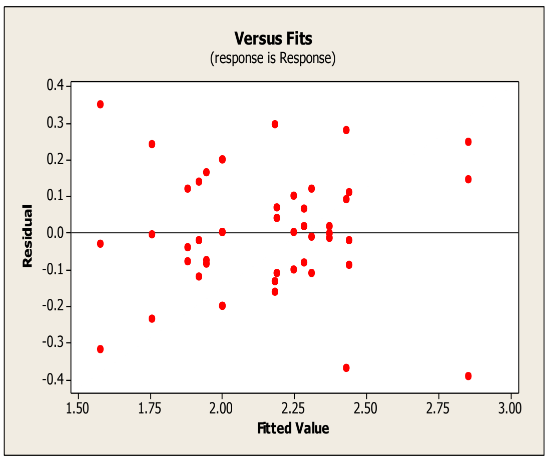

Figure 8. Plot of residual versus fitted value

3. *Confirmation*

The optimum solution by the regression model is calculated. The optimum point is one that in which all of the factors is at their high level. The regression model should be confirmed at the achieved optimum point. To confirm the regression model the experiment should be ran at the optimum point predicted by the regression model. After that the result of experiment is compared with the result of regression model. Table IV shows the result of three experiments at the optimum point predicted by the regression model. Variation between the result of experiment and regression model outcome is less than 10 % that is acceptable.

Table IV. RESULT OF CONFIRMATION TEST

Replicate	**1**	**2**	**3**	**Average of the Actual Response**
Actual Response	*2.52*	*2.73*	*2.55*	*2.6*
Predicted Response	*2.76*			
Variance (%)	$\frac{2.76-2.6}{2.76}$ *(100)=5.8%*			

B. *RSM performing*

Having done fractional factorial experiment for the paper helicopter, significant factors are Wing Length (C) and Body Length (D). The following table shows the data of the significant factors.

Table V. DATA OF SIGNIFICANT FACTORS

	Levels			
Factor	**High (1)**	**Center (0)**	**Low (-1)**	**Range**
Wing Length	100	90	80	20
Body Length	100	90	80	20

At phase 1, the process is going to be improved through the method “Path of Steepest Ascent (POSA)”. To do so, the other insignificant factors are set in such a way that can lead to better helicopter flight time. The insignificant factors are paper type, paper clip, and body width for which the best level that lead to best response are 70 grams, 1, and 20 millimeter (mm), respectively. For each run, the experiment is replicated 4 times. And a center point is also considered for which the experiment is replicated three times.

Table VI. PROCESS DATA FOR FITTING THE FIRST ORDER MODEL

Run	Natural Variables		Coded Variables						
	Body Length	Wing Length	Body Length	Wing Length	Response				
	ξ_1	ξ_2	X_1	X_2	R_1	R_2	R_3	R_4	$\bar{R}$
1	80mm	80mm	-1	-1	3	3.1	2.8	3.1	3
2	100mm	80mm	1	-1	2.5	2.9	2.6	3	2.7
3	80mm	100mm	-1	1	2.9	3	3.1	3	3
4	100mm	100mm	1	1	2.8	2.9	3	3.1	2.9
5	90mm	90mm	0	0	2.8	3	3.1		2.9

In this experiment, the coded variables are defined as below:

$$X_1 = \frac{\xi_1 - 90}{10} \quad (2)$$

$$X_2 = \frac{\xi_2 - 90}{10} \quad (3)$$

The regression model obtained for initial estimation of response surface is as below [3]:

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \quad (4)$$

In the above Equation, the parameters β_0, β_1 and β_2 are calculated as follows:

$\beta_0 = \frac{1}{19}$ (3 + 3.1 + 2.8 + 3.1 + 2.5 + 2.9 + 2.6 + 3 + 2.9 + 3 + 3.1 + 3 + 2.8 + 2.9 + 3 + 3.1 + 2.8 + 3 + 3.1) = 2.9316

$\beta_1 = \frac{1}{2} * \frac{1}{8}$ (2.5 + 2.9 + 2.6 + 3 + 2.8 + 2.9 + 3 + 3.1 – 3 – 3.1 – 2.8 – 3.1 – 2.9 – 3 – 3.1 – 3) = - 0.075

$\beta_2 = \frac{1}{2} * \frac{1}{8}$ (– 3 – 3.1 – 2.8 – 3.1 – 2.5 – 2.9 – 2.6 – 3 + 2.9 + 3 + 3.1 + 2.8 + 2.9 + 3 + 3.1) = 0.07812

Having calculated the above parameters, the regression model is as below:

$$\hat{Y} = 2.9316 + -0.075X_1 + 0.07812X_2$$

The next step in the POSA method is defining the step size for each significant factor. According to our experience, it is concluded that decreasing the body length and increasing the wing length leads to increase in flight time.

Therefore, the step size for factor B, Body Length, is considered as 1cm=10mm. Thus, $\Delta X_i = 10$

For the other significant factor, the step size is calculated using the below formula [3]:

$$\Delta \mathbf{X}_j = \frac{\beta_j}{-\beta_i/\Delta \mathbf{X}_i} = \frac{0.075}{-0.07812/10} = -9.6$$

The new experiment can be presented as follows:

Table VII.NEW EXPERIMENTS

	Coded Variable		Natural Variable		Response
	X1	X2	ξ1	ξ2	
Origin	0	0	90mm	90mm	3.2
Δ=Step Size	10	-9.6			
Origin - 1 Δ			80mm	99.6	3.4
Origin - 2 Δ			70mm	109.2	3.5
Origin -3 Δ			60mm	118.8	3.6
Origin - 4 Δ			50mm	128.4	3
Origin - 5 Δ			40mm	138	1.9
Origin - 6 Δ			30mm	147.6	1.3

The highlighted area in the above table shows that the optimum point lies between this areas. Now, the optimum point is calculated using a second order model which refers to second order response surface. This is done in the phase 2. Table V shows the factors and their new levels.

Table VIII.NEW LEVELS

Factor	Levels		
	(1)	(0)	(-1)
Body Length	70	60	50
Wing Length	128.4	118.8	109.2

The basic experimental designs to estimate second-order response surface models are central composite designs. A two-dimensional central composite design is shown in Fig.9.

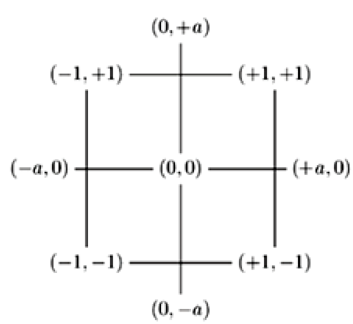

Figure 9. A two-dimensional central composite design

For the new experiment, the design can be presented as follows. The responses are achieved by running the experiment under the shown conditions:

Table IX.RESULT OF NEW EXPERIMENT

Run	Natural Variable		Coded Variable		Response
	Body Length	**Wing Length**	**Body Length**	**Wing Length**	
	ξ_1	ξ_2	X_1	X_2	
1	50	109.2	-1	-1	3.1
2	70	128.4	+1	-1	2.9
3	50	109.2	-1	+1	3.3
4	70	128.4	+1	+1	3.2
5	60	118.8	0	0	3.7
6	60	118.8	0	0	3.6
7	60	118.8	0	0	3.6
8	74.14	118.8	1.414	0	3.4
9	45.86	118.8	-1.414	0	3.3
10	60	131.045	0	1.414	3.4
11	60	106.55	0	-1.414	3.5

For the above experiment, the coded variables are:

$$X_1 = \frac{\xi_1 - 60}{10}$$

$$X_2 = \frac{\xi_2 - 118.8}{8.66}$$

The second order model can be written as follows [3]:

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \beta_{11} X_{11}{}^2 + \beta_{22} X_{22}{}^2 \quad (5)$$

Using Minitab, the estimated coefficient for β_0, β_1, β_2, β_{12}, β_{11} and β_{22} are 3.63, -0.0198, 0.0448, 0.025, -0.2104, and -0.1604, respectively. So the second order model is calculated as below:

$$\hat{Y} = 3.63 - 0.0198X_1 + 0.0448X_2 + 0.025X_1X_2 + 0.025X_{11}^2 - 0.2104X_{22}^2$$

Next the confirmatory experiment should be implemented. To do so, statistical software, Minitab, is used in which response optimizer is also applied for this purpose. To achieve the graphs, the lower level, target, and upper level are set to 3.1 seconds, 3.2 seconds, and 3.3 seconds, respectively. To do the confirmation, first, using response optimizer the optimum point that has the highest flight time is achieved. After that, the predicted flight time for the achieved optimum point is calculated by using the second order model. The experiment is run four times for the optimum point and the mean flight time is calculated. Then the mean and the predicted flight times are compared with each other to calculate the deviation. Using Minitab response optimizer, the following graph shows when the both factors D (body length 70mm) and E (wing length 107.32mm) are in high levels so the flight time is equal to=3.21sec (Fig.10).

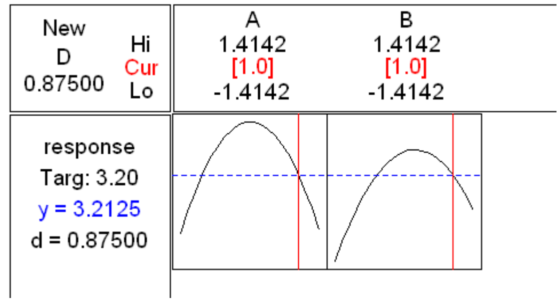

Figure 10. D at high and E at high

Another situation is when the factors D (body length, 50mm)is in low level and E (wing length, 107.32mm) is in high level the flight time is equal to=3.20sec (Fig.11).

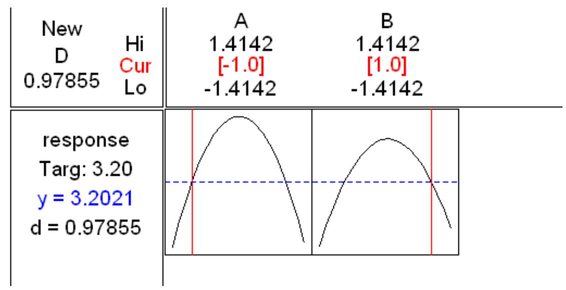

Figure 11. D at low and E at high

In addition when the factors D (body length 60mm)is in center level and E (wing length 115.98mm) is in center level the flight time is equal to=3.53sec and is the best point (Fig.12).

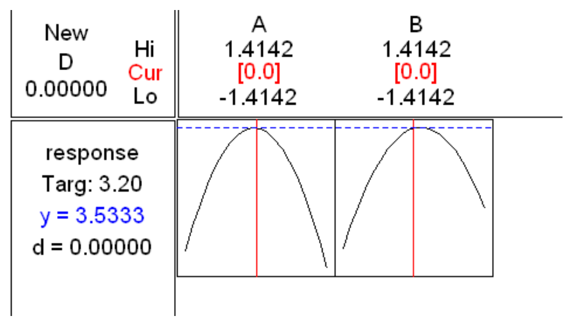

Figure 12. D and E at center

Fig.**13** illustrates that when the factors D (body length 70mm)is in high level and E (wing length 124.64mm) is in low level the flight time is equal to=3.07sec.

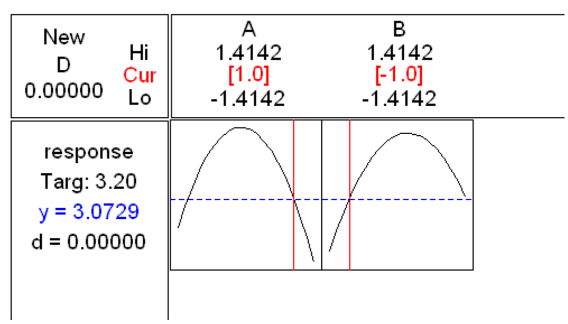

Figure 13. D at high and E at low

Fig.14 depicts that when the factor D is in α level and E is in center the flight time is equal to 3.08 sec.

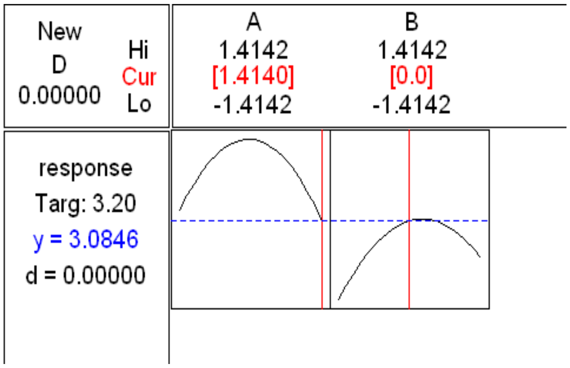

Figure 14. D at α level and E at center

Furthermore , when the factors D (body length 45.86mm)is in -α level and E (wing length 115.98mm) is in center the flight time is equal to=3.14sec (Fig.15)

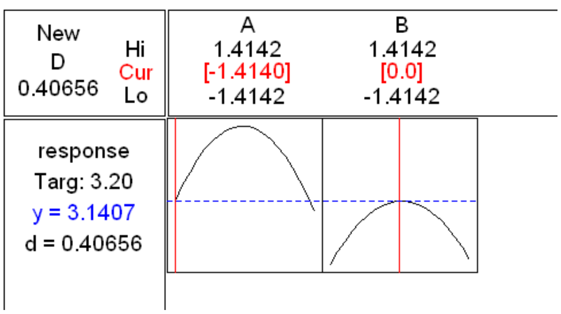

Figure 15. D at -α level and E at center

when the factors D (body length 60mm)is in center level and E (wing length 128.22mm) is in α level the flight time is equal to=3.27sec (Fig.16).

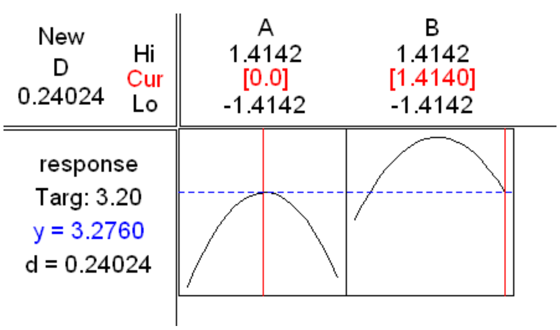

Figure 16. D at center and E at α level

The Fig. 17 shows that when the factors D (body length 60mm)is in center level and E (wing length 103.73mm) is in -α level the flight time is equal to=3.20sec.

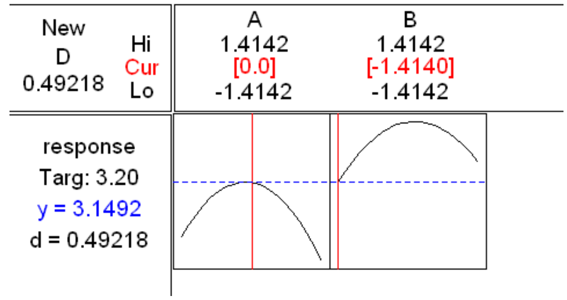

Figure 17. D at center and E at -α level

According to the figures, it is concluded that the best and optimum point is still the center point between the new levels. Table X shows a new design for factor D and E:

Table X. NEW DESIGN FOR FACTORS D AND E

Factor	Level		
	-1	0	1
D (Body Length)	50mm	60mm	70mm
B (Wing Length)	124.64	115.98	107.32

Regarding to the result on the top of the surface (Fig.18) the optimum point is 60mm for factor D (Body length) and 115.98mm for factor E (Wing length).Therefore, constructing a Paper Helicopter with the follow characteristics will get the practitioners the best response (Flight Time).

Table XI.OPTIMUM R ESULT OF EXPERIMENT

Factor	Characteristic
A (Paper type)	70gram
B (Paper clip)	1clip
C (Body width)	20mm
D (Body length)	60mm
E (Wing length)	115.98mm

To confirm the result, one paper helicopter with the above characteristics was built and launches it four times so the response was achieved as follow:

Table XII.RESULT OF CONFIRMATION EXPERIMENT

Run	Response
1	3.53sec
2	3.48sec
3	3.55sec
4	3.50sec

So it concluded that by launching the constructed Helicopter the response is the best. Furthermore If the coded (0, 0) was inserted instead of X_1 *and* X_2 in the second order regression model the 3.63 will achieved the in response. Therefore it is concluded that obtained response is confirmed.

$\hat{Y}$= 3.63 – 0.0198 X_1 + 0.0448 X_2 + 0.025 $X_1 X_2$ + 0.025 X_{11}^2 – 0.2104X_{22}^2

$\hat{Y}$= 3.63 – 0.0198 (0) + 0.0448 (0) +0.025 (0) (0) + 0.025 $(0)^2$ –0.2104 $(0)^2$ =3.63

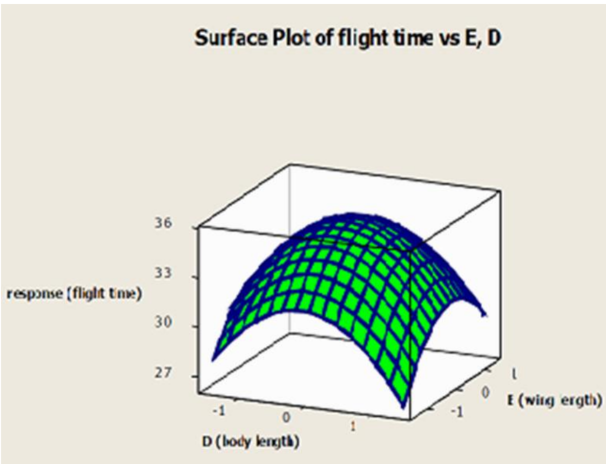

Figure 18. Estimated response surface for the coordinates of the maximum response

IV. CONCLUION

Design of experiment is one of the powerful tools with great capability in improving the performance of experiments. This paper has shown that application of design of experiment by industrial engineers is restricted due to lack of skills and knowledge. The paper concentrates on the wide gap in the knowledge needed by industrial engineers for understanding the major benefits of this problem solving method. The main goal of this paper is to bridge this gap by teaching combined one-half fractional factorial and response surface methodology to optimize the process performance. For simplicity the paper helicopter has been selected as a case study which is quite old and has been widely applied by many statisticians for teaching purpose. The experiment was conducted to optimize the paper helicopter flight time by considering the minimum number of trials. The results of this paper can stimulate the industrial engineers for wider application of DOE in real-life situations.

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