

Teaching Experimental Design Techniques to Industrial Engineers*

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Experimental Design (ED) is a powerful technique for understanding a process, studying the impact of potential variables or factors affecting the process and thereby providing spontaneous insight for continuous quality improvement possibilities. ED has proved to be very effective for improving the process yield, process capability, process performance and reducing process variability. However research has shown that the application of this powerful technique by the engineering fraternity in manufacturing companies is limited due to lack of skills and expertise in manufacturing, lack of statistical knowledge required by industrial engineers and so on. This paper illustrates some of the recent research findings on the problems and gaps in the state-of-the-art in ED. In order to bridge the gap in the statistical knowledge required by engineers, the article presents a paper helicopter experiment which can be easily carried out in a class-room to teach experimental design techniques. The results of the experiment have provided a greater stimulus for the wider application of ED by industrial engineers in real-life situations for tackling quality problems.

INTRODUCTION

EXPERIMENTAL DESIGN (ED) is a strategy of planning, conducting, analysing and interpreting experiments so that sound and valid conclusions can be drawn efficiently, effectively and economically. It provides the experimenters a greater understanding and power over the experimental process. ED has seen an increased application over fifteen years, as both manufacturing and service industries have attempted to refine and improve product, process and service quality. Experimental Design technology is not new to industrial and manufacturing engineers in today's modern business environment. ED was developed in the early 1920s by Sir Ronald Fisher at the Rothamsted Agricultural Field Research Station in London, England. After World War II, English practitioners of experimental design brought it to the US, where the chemical process industry was among the first to apply it [1].

A number of successful applications of ED for improving process performance, reducing process variability, improving process yield etc. have been reported by many manufacturers over the last fifteen years [2, 4]. Research has shown that the application of ED techniques by the engineering fraternity in both manufacturing and service industries is limited and when applied they are often performed incorrectly [5]. In other words, there is a cognitive gap in the knowledge of statistics required by engineers in using ED as a problem-solving tool. Moreover, the most

common remark made by many engineers is 'I can do the text book and class room examples but I am not comfortable while applying the concepts and principles of ED in my work area'. These findings point to the following issues [6]:

- Statistical education for engineers at university level is generally inadequate. The courses currently available in engineering statistics often tend to concentrate on the theory of probability, card shuffling, probability distributions and the more mathematical aspects of the subject rather than the techniques which are more practically useful to the engineering fraternity. Thus many engineers would deem statistics as useless in their late careers in industries.
- The lack of communication between the industrial and the academic worlds restricts the application of ED in many manufacturing and service industries.
- Lack of skills and expertise required by engineers in manufacturing, especially in problem formulation and definition.
- The existing methodologies in ED provide no insight into problem analysis and classification. Thus many engineers experience difficulties in analysing a particular process quality problem and then converting the engineering problem into statistical terms from which appropriate solutions can be chosen.
- Current software systems and expert systems in ED often tend to concentrate on data analysis and do not properly address interpretation of data. Thus many industrial engineers having performed the statistical analysis would not

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know what to do with the results without assistance from statistical consultants in the field.

BENEFITS OF EXPERIMENTAL DESIGN

ED enables industrial engineers to study the effects of several variables affecting the response or output of a certain process [7]. ED methods have wide potential application in the engineering design and development stages. It is the strategy of the management in today's competitive world market to develop products and processes insensitive to various sources of variation using ED. The potential applications of ED in industries are:

- reducing product and process design and development time;
- studying the behaviour of a process over a wide range of operating conditions;
- minimising the effect of variations in manufacturing conditions;
- understanding the process under study and thereby improving its performance;
- increasing process productivity by reducing scrap, rework etc.;
- improving the process yield and stability of an on-going manufacturing process;
- making products insensitive to environmental variations such as relative humidity, vibration, shock and so on;
- studying the relationship between a set of independent process variables (i.e., process parameters) and the output (i.e., response).

The following steps are useful while one may be performing an industrial experiment;

1. Definition of the objective of the experiment.
2. Selection of the response or output.
3. Selection of the process variables or design parameters (control factors), noise factors and the interactions among the process variables of interest. (Noise factors are those which cannot be controlled during actual production conditions, but may have strong influence on the response variability. The purpose of an experimenter is to reduce the effect of these undesirable noise factors by determining the best factor level combinations of the control factors or design parameters. For example, in an injection moulding process, humidity and ambient temperature are typical noise factors.)
4. Determination of factor levels and range of factor settings.
5. Choice of appropriate experimental design.
6. Experimental planning.
7. Experimental execution.
8. Experimental data analysis and interpretation.

PAPER HELICOPTER EXPERIMENT

The following section describes the application of ED for optimising the time of flight of a paper helicopter which can be made from A4-size paper. The experiment was carried out by the first author in a class-room for a post-graduate course in quality management at University of Portsmouth. The experiment requires paper, scissors, ruler, paper clips and a measuring tape. It would take

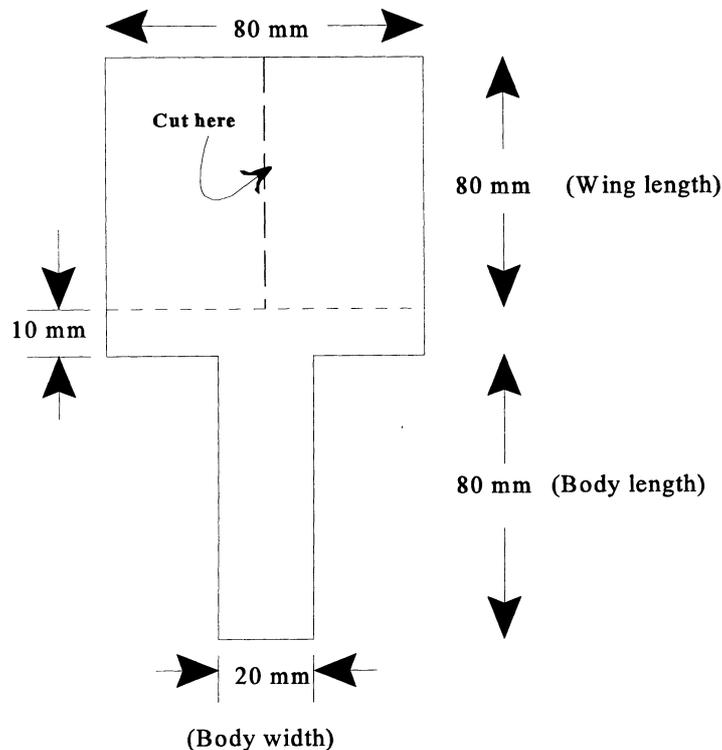


Fig. 1. Model of a paper helicopter design.

about 5–6 hours to design the experiment, collect the data and then perform appropriate statistical analysis. The model of a paper helicopter design is shown in Fig. 1.

The objective of the experiment was to determine the optimal settings of the design parameters which would maximise the time of flight. For the application of ED in solving process and product quality problems, it is essential that the objective of the experiment must be specified clear, brief and concise. Having defined the objective of the experiment, the possible parameters which might influence the time of flight were determined through a thorough brainstorming session. These parameters were then classified into control parameters and noise parameters. Control parameters are those which can be controlled easily by the operator during the experiment. For example, shrinkage of parts in an injection moulding process is quite critical, as it badly affects the final assembly. The control factors which might have an impact on the parts shrinkage are screw speed, mould temperature, cycle time and mould pressure. Noise parameters are those which are hard to control or expensive to control by the operator during the experiment [8]. For example in the above process, relative humidity is a noise factor.

The following control parameters were selected for the paper helicopter experiment:

- paper type
- wing length
- body width
- body length
- number of clips attached
- wing shape.

The two noise factors which could not be directly controlled during the experiment were:

- draft
- operator.

In order to minimise the effect of these noise factors on the time of flight, extra caution was taken during the experiment. For instance, the experiment was conducted in a closed room in order to dampen the effect of draft. The same person (i.e., operator) was responsible to minimise the reaction time of hitting the stopwatch when the helicopter is released and when it hits the floor.

Once the design parameters are selected, the next stage is to determine the number of levels in which the parameters should be studied for the

experiment. The level of a parameter is the specified value of a setting. For example, in the above injection moulding experiment, 210°C and 250°C are the low and high levels of mould temperature. It was decided to set each parameter at two levels or values as this forms the building block for studying parameters at three and higher levels. Design or process parameters at three levels are more complicated to teach in the first place and moreover the authors strongly believe that it might turn off engineers from learning ED any further [9]. It is usually best to experiment with the largest range feasible to observe the effect of a design parameter on the output or response. Here effect refers to the change in average response when a design (or process) parameter goes from a low level to a high level.

Table 1 illustrates the list of control parameters and their selected ranges for the experiment. In the context of ED, a ‘response’ is the quantity an experimenter wants to measure during the experiment in order to judge the performance of the product. In this case the response or performance monitored is the time of flight measured in seconds. Note that selection of an appropriate response for any industrial experiment is critical for its success [10]. For teaching purposes, it is good practice to choose continuous responses (e.g. surface roughness, strength, efficiency, life, etc.) than those which are attributes (e.g. taste, colour, appearance etc.).

Interactions of interest

Two factors, say, X and Y are said to interact with each other if the effect of control parameter X on the response (or output) is different at different levels of control parameter Y or vice versa [11]. If the effect of control parameter X on the response is the same at all levels of control parameter Y, then the interaction between the control parameters is said to be zero.

For industrial experiments with two control parameters X and Y considered at two levels (referred to as 2-level parameters), the interaction effect can be computed by the equation:

$$\begin{aligned} \text{Interaction effect} = & \frac{1}{2}(\text{Effect of control parameter} \\ & X \text{ at high level of } Y \\ & - \text{Effect of control parameter} \\ & X \text{ at low level of } Y) \end{aligned}$$

Table 1. List of control parameters for the experiment

Control parameters	Parameter labels	Low level (-1)	High level (+1)
Paper type	A	Normal	Bond
Wing length	B	80 mm	130 mm
Body width	C	20 mm	35 mm
Body length	D	80 mm	130 mm
No. of clips	E	1	2
Wing shape	F	Flat	Angled 45 up

or

$$\begin{aligned} \text{Interaction effect} &= \frac{1}{2}(\text{Effect of control parameter} \\ &\quad Y \text{ at high level of } X \\ &\quad - \text{Effect of control parameter} \\ &\quad Y \text{ at low level of } X) \end{aligned}$$

Choice of experimental design and design matrix for the experiment

The choice of experimental design depends on the number of degrees of freedom associated with main and interaction effects and cost and time constraints. Here the degrees of freedom is the number of independent and fair comparisons that can be made from a set of observations [12]. For example, if a control parameter is set as 2-level, then only one fair and independent comparison between the levels (i.e., low and high) can be made. For a control parameter at 3-level, the number of fair and independent comparisons that can be made among the levels is two. Therefore, the number of degrees of freedom associated with a control parameter at p levels is $(p - 1)$. The number of degrees of freedom associated with an interaction is the product of the number of degrees of freedom associated with each main effect involved in the interaction. For example, if a control parameter X is at 2-level and another control parameter Y at 3-level, then the number of degrees of freedom associated with their interaction is 2 (i.e., 1×2).

For the helicopter experiment, as we are interested in studying six main effects and three interaction effects, the total number of degrees of freedom is equal to nine (i.e., $6 + 3$). It is important to meet the criterion that the number of experimental trials required for a certain experiment must be greater than the number degrees of freedom associated with the main and interaction effects to be studied for the experiment. A factorial experiment is an experiment where one may vary

all the control parameters (or factors) in the experiment at their respective levels simultaneously [13]. A factorial experiment can be either full factorial or fractional factorial. A full factorial experiment (usually represented by 2^k) is preferred when both main and interaction effects are to be evaluated independently. The standard number of experimental trials or runs for a factorial experiment are 4, 8, 16, 32, 64 and so on. This can be easily derived using the formula: Number of experimental trials = 2^k where k is the number of control parameters at 2-level.

However, in many situations this type of experiment may be not feasible and practical due to time and cost constraints. Under such circumstances, fractional factorial experiments provide a reasonable alternative that still allows the experimenters to evaluate main effects [14]. Fractional factorial experiment will consume only a fraction of the full factorial experiment and is generally represented by $2^{(k-l)}$, where $\frac{1}{2}^l$ yields the fraction. For example, $2^{(5-2)}$ implies that the experimenter wishes to study five control parameters in eight experimental trials. This is a $\frac{1}{4}$ of a full factorial experiment (i.e., 2^5). For more information on fractional factorial experiments, the readers are advised to consult [15].

For the helicopter experiment, as the total number of degrees of freedom is equal to nine, the closest number of experimental trials that can be employed for the experiment is 16 (i.e., $2^{(6-2)}$ fractional factorial). This implies that only a quarter replicate of a full factorial experiment is needed for the study. The experiment was performed based on the design matrix as shown in Table 2. Each trial was randomised to minimise the effect of noise. Randomisation is a method of safeguarding the experiment from systematic bias which causes variation in response or output.

The design matrix displays all the control parameter settings for the experiment. Having constructed the design matrix, the flight times were recorded (see Table 2) corresponding to each trial condition.

Table 2. Design matrix for the helicopter experiment: () represents the experimental trials in random order

Trial no./run	A	D	B	C	E	F	Time of flight (s)
1 (6)	Normal	80	80	20	1	Flat	2.49
2 (9)	Bond	80	80	20	2	Flat	1.80
3 (11)	Normal	130	80	20	2	Angled	1.82
4 (15)	Bond	130	80	20	1	Angled	1.99
5 (12)	Normal	80	130	20	2	Angled	2.11
6 (2)	Bond	80	130	20	1	Angled	1.96
7 (16)	Normal	30	130	20	1	Flat	3.19
8 (14)	Bond	130	130	20	2	Flat	2.27
9 (10)	Normal	80	80	35	1	Angled	2.12
10 (1)	Bond	80	80	35	2	Angled	1.58
11 (7)	Normal	130	80	35	2	Flat	2.15
12 (3)	Bond	130	80	35	1	Flat	2.05
13 (8)	Normal	80	130	35	2	Flat	2.60
14 (4)	Bond	80	130	35	1	Flat	2.09
15 (5)	Normal	130	130	35	1	Angled	2.63
16 (13)	Bond	130	130	35	2	Angled	2.18

Table 3. Coded design matrix for the helicopter experiment

Trial no./run	A	D	B	C	E	F	Time of flight (s)
1 (6)	-1	-1	-1	-1	-1	-1	2.49
2 (9)	+1	-1	-1	-1	+1	-1	1.80
3 (11)	-1	+1	-1	-1	+1	+1	1.82
4 (15)	+1	+1	-1	-1	-1	+1	1.99
5 (12)	-1	-1	+1	-1	+1	+1	2.11
6 (2)	+1	-1	+1	-1	-1	+1	1.96
7 (16)	-1	+1	+1	-1	-1	-1	3.19
8 (14)	+1	+1	+1	-1	+1	-1	2.27
9 (10)	-1	-1	-1	+1	-1	+1	2.12
10 (1)	+1	-1	-1	+1	+1	+1	1.58
11 (7)	-1	+1	-1	+1	+1	-1	2.15
12 (3)	+1	+1	-1	+1	-1	-1	2.05
13 (8)	-1	-1	+1	+1	+1	-1	2.60
14 (4)	+1	-1	+1	+1	-1	-1	2.09
15 (5)	-1	+1	+1	+1	-1	+1	2.63
16 (13)	+1	+1	+1	+1	+1	+1	2.18

STATISTICAL ANALYSIS AND INTERPRETATION OF RESULTS

Having obtained the response values, the next step is to analyse and interpret the results so that necessary actions can be taken accordingly. The first step in the analysis involves the computation of both main and interaction effects. For computation purposes, the low and high levels in the design matrix (refer to Table 2) must be replaced by -1 and $+1$ respectively. For example, control parameter 'A' column must be replaced by -1 , $+1$, -1 , $+1$ and so on. The same procedure must be applied to other control parameters. The resulting coded design matrix for the experiment is shown in Table 3. This table is used for all computations of main and interaction effects.

Calculation of main effects

The effect of a main/interaction effect is the difference in the average response at low and high levels. For example, the effect of control parameter A can be calculated as follows:

- Average time of flight at high level of A = 1.99
- Average time of flight at low level of A = 2.39
- Effect of control parameter A = $2.39 - 1.99 = -0.40$

A negative sign indicates that the slope of the line connecting the low and high values is negative. In other words, the average time of flight at the low level is higher than that at the high level. Similarly, the effects of other control parameters can be

Table 4. Table for main effects for the experiment

Control parameters	Average at high level	Average at low level	Effect
A	1.99	2.39	-0.40
D	2.29	2.09	0.20
B	2.38	2.00	0.38
C	2.20	2.18	0.02
E	2.06	2.32	-0.26
F	2.04	2.34	-0.30

estimated. Table 4 illustrates the estimated main effects for the experiment.

In order to assist people with limited mathematical skills, the authors recommend a graphical plot of main effects. The notion behind the use of this graphical representation is to provide novices a better picture on the importance of the effects of the chosen control parameters. Figure 2 illustrates the main effects plot of the control parameters.

The main effects plot shows that the most dominant control parameter on the time of flight is paper type, followed by wing length, wing shape and number of clips. The control parameter body width has no impact on the time of flight.

Calculation of interaction effects

For the helicopter experiment, we were interested to study the following three interactions:

- Wing length Body width ($B \times C$)
- Wing length Body length ($B \times D$)
- Paper type Number of clips ($A \times E$)

Consider the interaction between the control parameters B and D. In order to compute the interaction, we must obtain the average time of flight at each level combination of these control parameters. There are all together four combinations of levels between these two parameters:

$B_{-1}D_{-1}$, $B_{-1}D_{+1}$, $B_{+1}D_{-1}$ and $B_{+1}D_{+1}$. The average time of flight at these combinations are illustrated in Table 5.

Interaction effect ($B \times D$)

$$\begin{aligned}
 &= \frac{1}{2}(\text{Effect of } B \text{ at high level of } D \\
 &\quad - \text{Effect of } B \text{ at low level of } D) \\
 &= \frac{1}{2}[(2.568 - 2.003) - (2.190 - 1.998)] \\
 &= 0.187
 \end{aligned}$$

An alternative approach for computing the interaction effect between B and D can be achieved by multiplying the coded levels of B and D in each

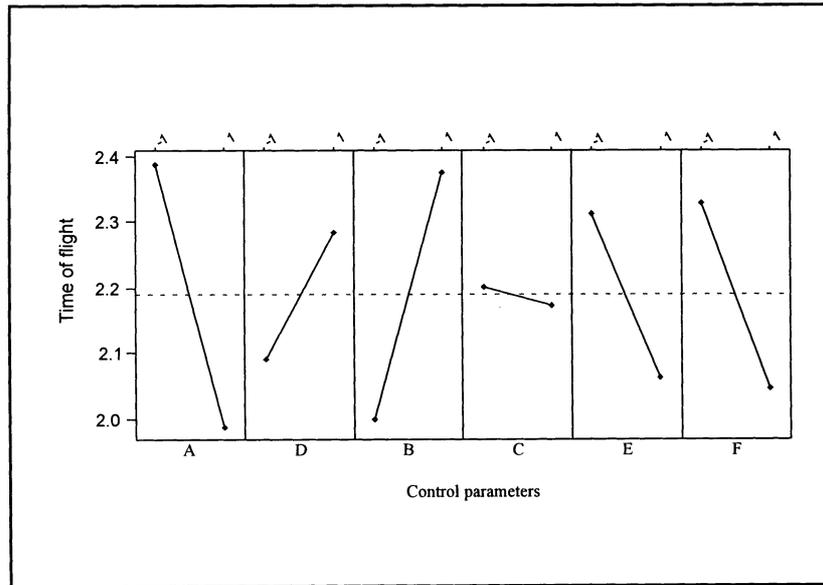


Fig. 2. Main effects plot of the control parameters.

row of Table 3. Having obtained the levels for the product ($B \times D$), we will then calculate the average flight times corresponding to low and high levels of ($B \times D$). The interaction effect between B and D can now be estimated in a similar manner to the main effects:

Interaction effect ($B \times D$)

$$= \text{Average flight time at high level of } (B \times D) - \text{Average flight time at low level of } (B \times D)$$

Similarly, the interactions between B and C, i.e., ($B \times C$), and the interaction between A and E, i.e., ($A \times E$) can be computed. The results are summarised in Table 6.

Interaction plot

This is a very powerful graphical tool for interpreting the interaction effects. It provides a better and rapid understanding of the nature of interactions among the control parameters under consideration. Non-parallel lines in the interaction plot connote the existence of interaction among the parameters, whereas parallel lines indicates the non-existence of interaction among the parameters for investigation. Consider the interaction between wing length (B) and body length (D) for the above experiment. The interaction plot is shown in Fig. 3. As the lines are non-parallel, there is an interaction between the control parameters B and D.

Table 5. Average response table

B	D	Average time of flight
-1	-1	1.998
-1	+1	2.003
+1	-1	2.190
+1	+1	2.568

The main effects plot and interaction plot however does not tell us which of the main and/or interaction effects are statistically significant. Under such circumstances, it is good practice to employ normal probability plots [16]. For normal probability plots, the main and interaction effects of control parameters should be plotted against cumulative probability (%). Inactive main and interaction effects tend to fall roughly along a straight line whereas active effects tend to appear as extreme points falling off each end of a straight line. These active effects are judged to be statistically significant. Figure 4 shows a normal probability plot of effects (both main and interaction) of control parameters at 99% confidence level (or 1% significance level). Here significance level is the risk of saying that a factor is significant when in fact it is not. In other words, it is the probability of the observed significant effect (either main or interaction) being due to pure chance. For experimental design problems, we generally consider both 5% and 1% significance levels. If α measures the significance level, then $(1 - \alpha)$ measures our confidence for an effect to be statistically significant [17]. The graph (Fig. 4) shows that main effects A, B, E and F are statistically significant. The interaction between B and D was not statistically significant at 1% significance level (or 99% confidence level) though it appeared to be important in the interaction graph (refer to Fig. 3).

Table 6. Table of interaction effects

Interaction effects	Estimate of the effect
$B \times D$	0.187
$B \times C$	0.021
$A \times E$	0.186

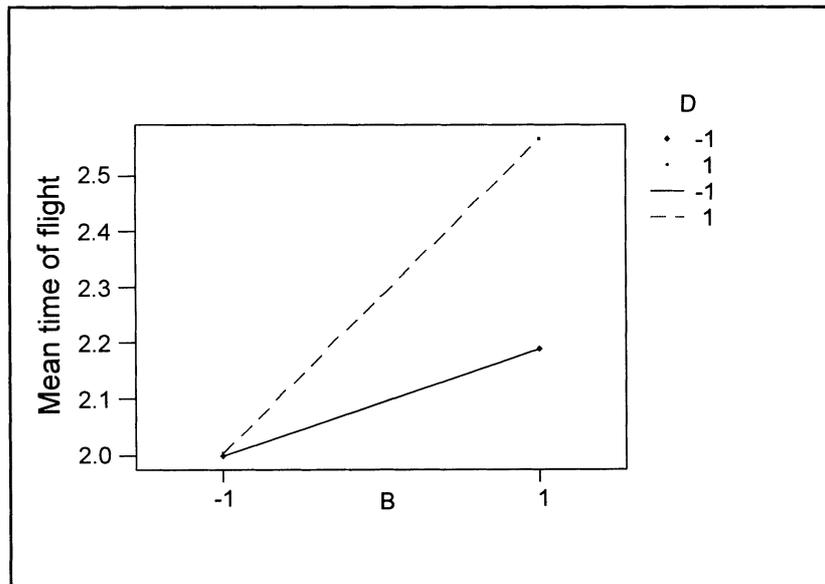


Fig. 3. Interaction plot between parameters B and D.

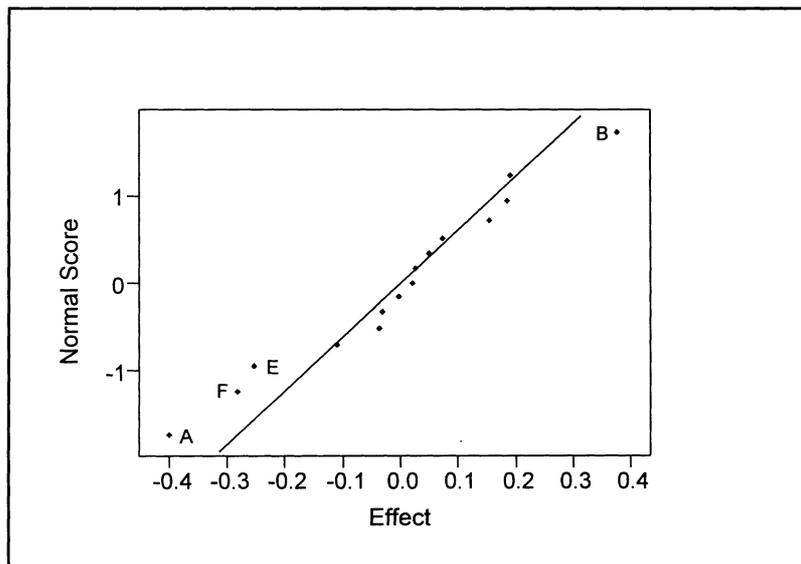


Fig. 4. Normal probability plot of effects.

Determination of optimal control parameter settings

Having identified the significant control parameters, the next step is to determine the optimal settings of these parameters that will maximise the flight time. In order to arrive at the optimal condition, the mean time of flight at each level of these parameters was analysed. As none of the interaction effects were statistically significant, the main concern was the average flight times at the low and high level of the main effects (refer to Table 4). From Table 4, the final optimal settings of control parameters was derived (see Table 7). It is quite interesting to notice that the optimal control parameter settings is one which correspond to trial condition 7 (see Table 2). The time of flight was maximum when wing length and body length

were kept at high levels. A confirmatory experiment was carried out to verify the results from the analysis. Five helicopters were made based on the optimal combination of control parameter levels. The average flight time was estimated to be 3.26 s.

Table 7. Final optimal control parameter settings

Control parameters	Optimum level
Paper type	Normal (low level)
Wing length	130 mm (high level)
Body width	20 mm (low level)
Body length	130 mm (high level)
Body length	130 mm (high level)
Number of clips	1 (low level)
Wing shape	Flat (low level)

Significance of the work

The purpose of this section is to bring the importance of teaching experimental design techniques to engineers with limited statistical skills for tackling quality engineering problems in many organisations. It is quite important to note that this experiment is quite old in its nature and has already been widely used for some time by many statisticians for teaching purposes. Nevertheless the focus here was to minimise the statistical jargon associated with the technique and bring modern graphical tools for better and rapid understanding of the results to non-statisticians.

This experiment was conducted in a class-room to help students come to grips with experimental design. As it is an extremely simple experiment, the concept and the objective of the experiment was quite straight forward. The students of the class found this particular experiment interesting specifically in terms of selecting the appropriate experimental design, conducting the experiment and interpreting the results of the experiment. Many students were quite astounded with the use of graphical tools and its reduced involvement of number crunching. The experiment helped them to understand the importance of brainstorming for identifying the key variables and understanding the concept and nature of interactions among the variables. The authors strongly believe that the experiment provided a simple and beneficial way to help students view on experimental design in a more approachable manner which consequently led to their eagerness to apply it in their own work environment. As many of the students had marketing background, they commented that

experimental design could be applied in reducing the cycle time for new products, maximising the response for a certain advertisement and comparing competitive strategies and decision-making processes.

CONCLUSIONS

Experimental design is a very powerful problem-solving technique that assists industrial engineers for tackling quality control problems effectively and economically. Research has shown that the application of ED by industrial engineers is limited due to lack of skills in manufacturing and lack of statistical knowledge. The paper illustrates the cognitive gap in the knowledge required by industrial engineers for understanding the potential benefits of this powerful-problem solving technique. The purpose of this paper is to bridge this gap by illustrating a simple experiment which can be easily carried out in a room to teach experimental design techniques to engineers. In order to keep the experiment simple, all the control parameters were studied at 2-level. The authors believe that control parameters at 2-level will form a firm foundation for studying the parameters at 3-level and higher. The results of the experiment has provided a greater stimulus for the wider application of ED by industrial engineers in real-life situations.

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