# ISEN 616: Design and Analysis of Industrial Experiments

**Optimization of Design of a Paper Helicopter to Increase its Flight time**

**Project Report**

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**Content Table**

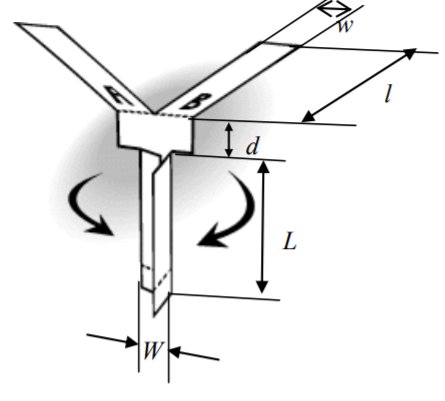
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**Abstract**:

The objective of the experiment is to increase the flight time of the paper helicopter by optimizing its structural design. This is done by selecting significant factors and their appropriate level setting for achieving this objective. In order to design the matrix, we use the Plackett-Burman Design. Significant factors and their level settings are identified using two approaches – Half-normal plot and Hamada Wu analysis. A comparison is done based on the results obtained from both these approaches and validation is performed by using the identified significant factors and their level settings. The factors considered here are the length of the wing(l), width of the wing(w), length of the body(L), width of the body(W), Middle body length(d), and the fold at the tip(F) which can be denoted as the figure below:

**Introduction:**

In this project we use Plackett-Burman design OA(12,211) (Figure 2) for constructing a design matrix. OA(12,26) design is used for this experiment as 6 factors are considered. 12 paper helicopters are crafted using the design notations mentioned in Figure 1 and design matrix(Table 2) and factors and their level mentioned in Table 1.



***Figure1****: Paper Helicopter Structural Design*

***Table1****: The factors and levels of paper helicopter are considered as follows –*

|  |  |  |  |
| --- | --- | --- | --- |
| Factors | Symbol | Dimensions | |
| - level | + level |
| Wing length | l | 3 inches | 4.5 inches |
| Wing width | w | 1.8 inches | 2.4 inches |
| Body length | L | 3 inches | 4.5 inches |
| Body width | W | 1.25 inches | 2 inches |
| Middle body length | d | 1 inch | 1.5 inches |
| Fold at tip | F | no | yes |

The **first** approach in this experiment is to identify significant factors and effects using half-normal plot. It is a graphical tool that uses these ordered estimated effects to help assess which factors are significant.

The half-normal plot consists of the points –



where,

≤ . . . . . . ≤ = ordered values of the factorial effect

φ = cumulative distribution function of a standard normal variable.

I = number of effects and interaction of effects considered.

Half Normal Plot Analysis approach will be discussed later in this report.

The **second** approach is to identify significant effects using Hamada Wu analysis.

Hamada Wu analysis is based on effect sparsity principle and effect heredity principle. Effect sparsity principle states that the number of relatively important effects in a factorial experiment is small. i.e. we try to determine the important factors from the considered factors (such as l,W,w….) which would greatly affect the flight time of the Paper Helicopter.

While effect heredity principle states that in order for interaction to be significant, at least one of its parent main effects should be significant. i.e. we would consider the interaction effect of two factors only if one of its component parent factor is obtained significant.

![A picture containing table

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*Figure 2: Plackett Burman Design*

For experiments based on designs with complex aliasing, it is difficult to disentangle the large number of aliased effects and to interpret their significance. For this reason, such designs were traditionally used for screening factors only-that is, to estimate factor main effects but not their interactions.

The validity of the main effect estimates for screening designs depends on the assumption that the interactions are negligible. In many practical situations this assumption is often questionable, which suggests the need for strategies that allow interactions to be entertained

The Complex aliasing pattern can be greatly simplified under the assumption of effect sparsity that number of relatively important factors are small and effect hierarchy principle which signifies that main effects are more important than interaction effects.

Traditionally complex aliasing was considered as a disadvantage as it involved many possible models which were hard to discriminate.

Thus, Hamada and Wu suggested a method of using this complex aliasing to our advantage for design of experiment.

We can apply the Hamada Wu strategy when effect sparsity and effect heredity principles hold and the correlations between partially aliased effects are small to moderate. We use the same methods as the variable selection techniques for Hamada Wu but with modification considering that design should work also when the number of effects is more than number of runs.

**Method:**

**1.** **A** **Design Matrix:**

Here the widely used experimental design which is the Plackett Burman Design is considered. It consists of 12 runs and 6 factors(l,w,W,F,L,d) with two levels as high and low for this experiment.

The principles of randomization and replication are used while designing the experiment.

Randomization – The Plackett-Burman design consist of 11 factors out of which 6 have been chosen for this experiment randomly using the following R-code –

Randomization for factors:

sample(1:11, 6, replace=FALSE)

1,11,2,10,7,3,4,8,9,5,6

Randomization along 12 runs:

sample(1:12, 12, replace=FALSE)

3,4,1,10,11,9,12,2,7,5,8,6

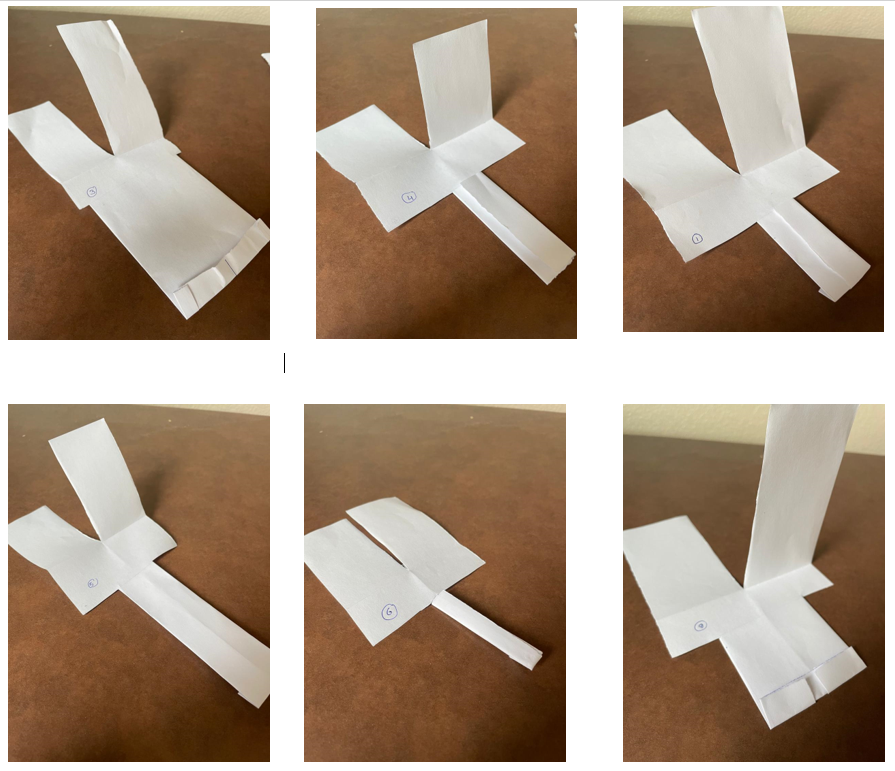
Replication – 3 replicates were considered as y1, y2, y3 by dropping the paper helicopter for a given run from a fixed height and the flight time was noted down three times using a stopwatch.

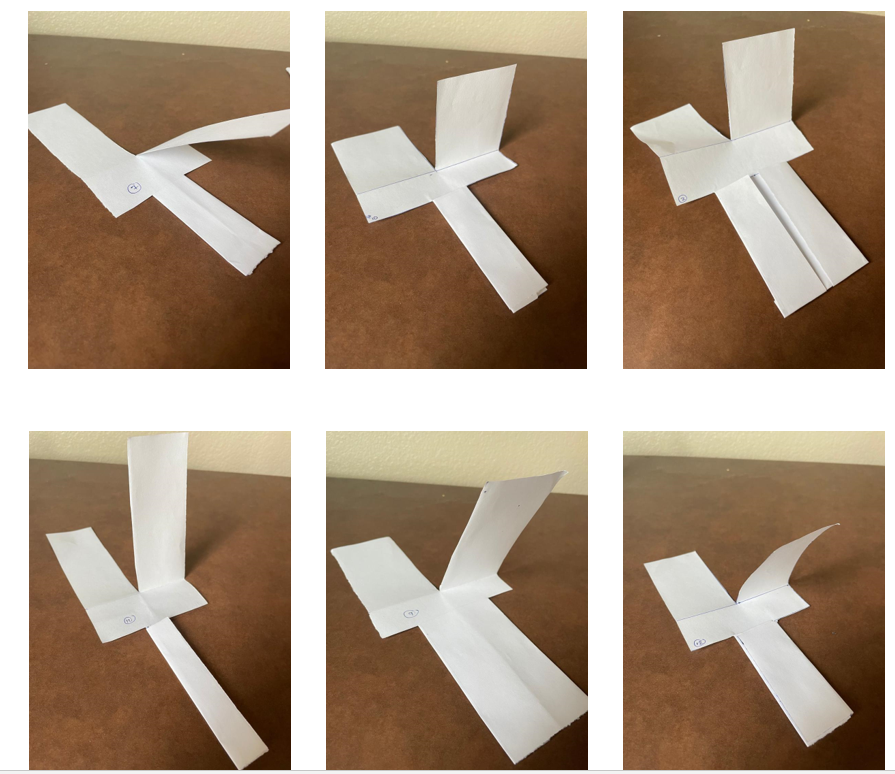
*Table 2- Design Matrix:*

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **runs** | **l** | **w** | **L** | **W** | **d** | **F** | **4** | **8** | **9** | **5** | **6** |
| 1 | + | - | + | + | - | - | + | - | - | + | + |
| 2 | - | + | + | - | + | + | - | - | - | + | + |
| 3 | + | - | - | - | + | + | + | + | - | - | + |
| 4 | - | - | + | - | + | - | + | + | + | + | - |
| 5 | - | - | - | + | - | + | - | + | + | + | + |
| 6 | - | + | - | + | + | - | + | - | + | - | + |
| 7 | + | + | - | + | + | - | - | + | - | + | - |
| 8 | + | + | + | - | - | - | - | + | + | - | + |
| 9 | + | - | + | + | + | + | - | - | + | - | - |
| 10 | - | + | + | + | - | + | + | + | - | - | - |
| 11 | + | + | - | - | - | + | + | - | + | + | - |
| 12 | - | - | - | - | - | - | - | - | - | - | - |

**2. Crafting Paper Helicopters:**

12 Paper helicopters are crafted as per the factor levels mentioned in the design matrix.





*Figure 3: Image of Crafted Paper Helicopters*

Paper Helicopters are crafted by considering the following:-

The factor levels are chosen as per the table Table 2 shows the value of + level and – level of all the factors. For factor F(Fold at tip), the value of 0.2 inch corresponding to + level is used for all the runs and is kept constant throughout the experiment. The sheet of paper used is same for all the paper helicopters.

We consider an arbitrary height of 10 feet for dropping the helicopter and using a stopwatch to note the time taken by the helicopter to touch the ground. We perform these 3 replicates for each run and note down the readings. For this experiment the flight time of paper helicopter is considered as the response variables.

**3. Reading Observations:**

ybar values are the mean of replicates y1, y2, y3.

s2 values are the variance of replicates y1, y2, y3.

lns2 values are natural logarithm of the s2 values.

(Note: A primary reason for the log transformation is that it maps positive values to real (both positive and negative) values, and by taking its inverse transformation, any predicted value on the log scale will be transformed back to a positive value on the original scale. )

**4. Half-Normal Plot:**

Significant factors using Half-normal plot –

Half normal plot –

It is a probability plot which is a graphical tool that uses these ordered estimated effects to help assess which factors are significant.

Steps for plotting half-normal plot -

* The main effect values and interaction effect values are calculated.
* The absolute values of the main effect and interaction effect are ordered.
* The half-normal plot is plotted with ordered effect values on y-axis and half-normal quantities on x-axis.

Identifying significant effects -

Insignificant factors are those that have near-zero effects and significant factors are those whose effects are considerably removed from zero. Thus, insignificant effects tend to have a normal distribution centered near zero while significant effects tend to have a normal distribution centered at their respective true large (but unknown) effect values.

Steps –

1. identifying this line of near-zero (insignificant) factors; then
2. declaring the remaining off-line factors as significant.

**5. Hamada Wu:**

We use the forward selection technique to determine a group effects which are significant by applying the following steps:

Step 1: For each factor such as l,w,W,F,d,L we perform stepwise regression for each six models involving main effects and interaction plots. For instance for factor l we consider (l+lw+lW+lF,ld,lL) model for step 1.

Step 2: We select all the significant factors obtained from each model and develop a model which consists of all the main effects and the interaction effects as obtained from step 1. We again apply stepwise regression on this model.

Step 3: We select all the main effects and the interaction effects whose at least one component factor appears as a significant factor from step 2

Step 4: Iterate over step2 and step3 until the model stops changing.

**Analysis**

**1. Half-normal plot analysis** –

Half-normal plot for location effect –

The location effects are calculated for all the factor as follows –

ME(A) = z(A+) - z(A-)

where z(A+) is the average of the Zj values observed at A+ and z(A-) is similarly defined.

*Table 4: Location Effects*

Half-Normal Plot for Location Effects:

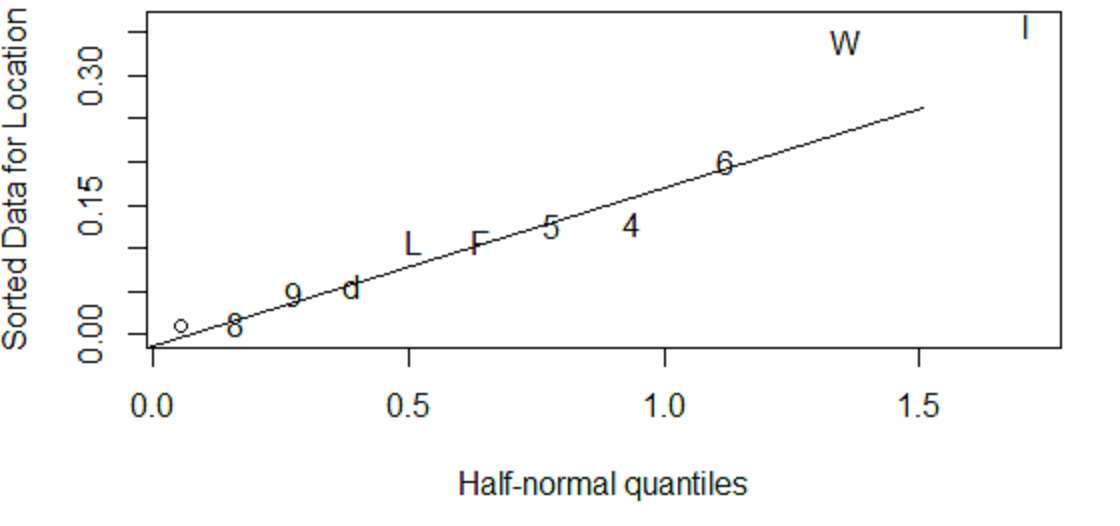
**R-Code:**

Half Normal Plot for Location Effects

setwd("C:/Meet College/616/Project")  
df = read.csv(file="Data(randomized).csv") #Insert the Directory in the CSV format  
#install.packages("faraway")  
library(olsrr)

library(faraway)

# For Location  
x = halfnorm(df$locationvalues, nlab = 10, labs = as.character(df$locationmaineffects), ylab = "Sorted Data for Location",)

 Figure 4: Half Normal Plot for Location effects

The half-normal probability of these effects is shown in the Figure 4. 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 is the main effect l (Wing length) and W (Body Width)

The R code for applying regression is as follows –

model = lm(ybar~W+l,data=df)  
summary(model)

##   
## Call:  
## lm(formula = ybar ~ W + l, data = df)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -0.27083 -0.05917 -0.00750 0.08792 0.33917   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2.53083 0.05289 47.854 3.81e-12 \*\*\*  
## W -0.16917 0.05289 -3.199 0.01085 \*   
## l 0.17917 0.05289 3.388 0.00803 \*\*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.1832 on 9 degrees of freedom  
## (18 observations deleted due to missingness)  
## Multiple R-squared: 0.7069, Adjusted R-squared: 0.6418   
## F-statistic: 10.85 on 2 and 9 DF, p-value: 0.003994

Thus from the above Half normal plot obtained for location effects we obtain W and l as significant main effects. Using Half Normal Plot we obtain an adjusted R^2 value of 64.18%

We get the following equation of significant factors for location effects:

y ̂ = 2.5308 – 0.1692 *xW* +0.1792 *xl*

Half-normal plot for **Dispersion**

The dispersion effects are calculated for all the factor as follows –

ME(A) = z(A+) - z(A-)

where z(A+) is the average of the Zj values observed at A+ and z(A-) is similarly defined.

*Table 5: Dispersion Effects*

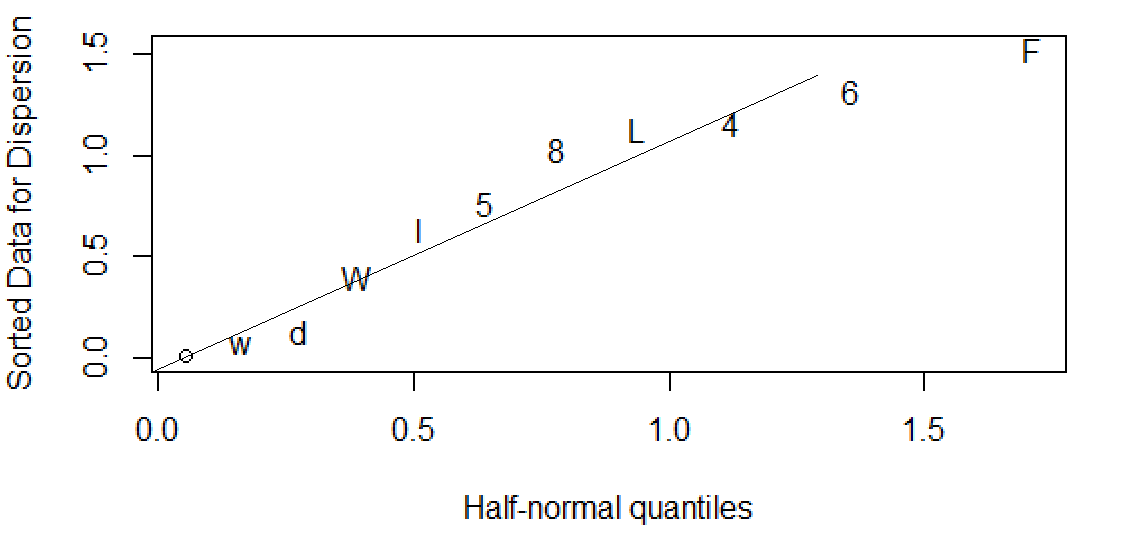


Half-Normal Plot for Dispersion Effects:

**R-Code:**

Half Normal Plot for Dispersion Effects

# For Dispersion  
y = halfnorm(df$dispersionvalues, nlab = 10, labs = as.character(df$dispersionmaineffects), ylab = "Sorted Data for Dispersion",)



model = lm(lns2~F,data=df)  
summary(model)

##   
## Call:  
## lm(formula = lns2 ~ F, data = df)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -1.4996 -0.8332 0.2520 0.5534 1.6636   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -4.0088 0.3055 -13.123 1.25e-07 \*\*\*  
## F -0.3294 0.3055 -1.078 0.306   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.058 on 10 degrees of freedom  
## (18 observations deleted due to missingness)  
## Multiple R-squared: 0.1042, Adjusted R-squared: 0.01457   
## F-statistic: 1.163 on 1 and 10 DF, p-value: 0.3062

Thus, from the above Half normal plot obtained for location effects we obtain only F(Fold at tip) as significant main effect. Using Half Normal Plot, we obtain an adjusted R^2 value of 1.457%

We get the following equation of significant factors for Dispersion effects:

lns2 = -4.0088 - 0.3294 *xF*

Here in order to reduce the dispersion(variance) we consider the setting of factor F(Fold at tip) as positive level i.e. Folding the tip at the end of the paper helicopter.

**2. Analysis for Half-Normal plot**

In order to increase the flight time of paper helicopter we minimize the variance of the design given by Eq.[2]

lns2 = -4.0088 - 0.3294 *xF*

Calculating by putting *F* = +1

lns2 = -4.3382

For minimizing variance,

Therefore, the setting for *F* should be taken as + level(Yes for the fold at tip) for minimizing the above equation.

Thus, it can be observed flight time(response variable) from Eq.[1] –

y ̂ = 2.5308 – 0.1692 *xW* +0.1792 *xl*

at *W(-)*and l(+) value of flight time(response variable) is maximized.

Calculating by putting *l* = +1, and W = +1

= 2.8792

Thus, maximum flight time using half-normal plot approach is 2.8792 seconds.

**3. Hamada Wu Approach:**

**R-Code:**

setwd("C:/Meet College/616/Project")  
df = read.csv(file="Data(randomized).csv") #Insert the Directory in the CSV format  
#install.packages("faraway")  
library(olsrr)  
library(faraway)

Now we apply the **Hamada-Wu** Analysis as below:

**Step 1**

# Hamada-Wu  
# For Location Effects  
  
#for factor l  
m1 = lm(ybar~l+lw+lL+lW+ld+lF ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m1)

##   
## Stepwise Selection Summary   
## -----------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## -----------------------------------------------------------------------------------  
## 1 l addition 0.374 0.311 4.7980 4.9826 0.2541   
## 2 lw addition 0.621 0.537 1.7380 0.9448 0.2082   
## 3 lF addition 0.748 0.653 1.1560 -1.9262 0.1803   
## -----------------------------------------------------------------------------------

# for factor w  
m2 = lm(ybar~w+wL+wW+wd+wF+lw ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m2)

##   
## Stepwise Selection Summary   
## -----------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## -----------------------------------------------------------------------------------  
## 1 lw addition 0.248 0.172 -1.3440 7.1844 0.2785   
## -----------------------------------------------------------------------------------

# for factor L  
m3 = lm(ybar~L+LW+Ld+LF+wL+lL ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m3)

##   
## Stepwise Selection Summary   
## -----------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## -----------------------------------------------------------------------------------  
## 1 LW addition 0.067 -0.026 -2.4900 9.7668 0.3101   
## -----------------------------------------------------------------------------------

# for factor W  
m4 = lm(ybar~W+Wd+WF+LW+wW+lW ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m4)

##   
## Stepwise Selection Summary   
## -----------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## -----------------------------------------------------------------------------------  
## 1 Wd addition 0.353 0.288 5.5260 5.3704 0.2582   
## 2 W addition 0.686 0.617 0.5590 -1.3154 0.1895   
## -----------------------------------------------------------------------------------

# for factor d  
m5 = lm(ybar~d+dF+Wd+Ld+wd+ld ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m5)

##   
## Stepwise Selection Summary   
## ----------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## ----------------------------------------------------------------------------------  
## 1 Wd addition 0.353 0.288 1.4980 5.3704 0.2582   
## ----------------------------------------------------------------------------------

# for factor F  
m6 = lm(ybar~F+dF+WF+LF+wF+lF ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m6)

##   
## Stepwise Selection Summary   
## -----------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## -----------------------------------------------------------------------------------  
## 1 lF addition 0.126 0.039 -1.4230 8.9778 0.3001   
## -----------------------------------------------------------------------------------

By performing Step 1 we get the following significant interactions: lF,LW,lw,Wd We consider this interaction effects along with all the main effects for performing step2

**Step 2**

#Step 2  
  
#Considering all significant factors obtained from step1  
m7 = lm(ybar~l+w+L+W+F+d+lF+LW+lw+Wd ,data=df) # Using step wise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m7)

##   
## Stepwise Selection Summary   
## -------------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## -------------------------------------------------------------------------------------  
## 1 l addition 0.374 0.311 13.9550 4.9826 0.2541   
## 2 W addition 0.707 0.642 4.2750 -2.1293 0.1832   
## 3 Wd addition 0.878 0.833 0.2600 -10.6929 0.1251   
## -------------------------------------------------------------------------------------

We obtain main effect l,W and interaction effect Wd as the significant factors by performing step 2. We consider all the main effects and interaction effects whose atleast 1 component main effect is significant as obtained from step 2 for performing step 3.

**Step3**

#Step 3  
  
#Considering all significant factors obtained from step2  
m8 = lm(ybar~l+W+WF+LW+wW+Wd+lW+lw+lL+lW+lF ,data=df) # Using step wise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m8)

##   
## Stepwise Selection Summary   
## -------------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## -------------------------------------------------------------------------------------  
## 1 l addition 0.374 0.311 88.8230 4.9826 0.2541   
## 2 W addition 0.707 0.642 39.3110 -2.1293 0.1832   
## 3 Wd addition 0.878 0.833 14.7890 -10.6929 0.1251   
## 4 WF addition 0.934 0.896 8.2080 -16.0135 0.0986   
## 5 wW addition 0.966 0.938 5.2050 -22.0956 0.0761   
## -------------------------------------------------------------------------------------

By performing Step 3 as above we get main effects l and W as significant. While we obtain Wd,WF,wW as significant interaction effects. Here we perform step 4 by repeating step 2 and 3 until we obtain the same model as obtained from previous step.

**Step4**

#Step 4   
#Considering all significant factors obtained from step1  
m9 = lm(ybar~l+w+L+W+F+d+Wd+wW+WF ,data=df) # Using step wise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m9)

##   
## Stepwise Selection Summary   
## -------------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## -------------------------------------------------------------------------------------  
## 1 l addition 0.374 0.311 61.8450 4.9826 0.2541   
## 2 W addition 0.707 0.642 26.6860 -2.1293 0.1832   
## 3 Wd addition 0.878 0.833 9.5540 -10.6929 0.1251   
## 4 WF addition 0.934 0.896 5.3640 -16.0135 0.0986   
## 5 wW addition 0.966 0.938 3.7550 -22.0956 0.0761   
## -------------------------------------------------------------------------------------

We obtain a similar model from step 4 as from step 3 we stop further iteration. Thus we obtain the final model by Hamada\_Wu analysis as l,W,Wd,WF,wW and an adjusted R^2 value as 93.8%

Applying regression analysis on these significant factors following output is obtained –

R-code for regression analysis –

ols\_step\_both\_p(m9)$model

Call:

lm(formula = paste(response, "~", paste(preds, collapse = " + ")),

data = l)

Coefficients:

(Intercept) wL w lw d

-4.0088 -0.4841 0.4676 0.5768 0.3929

W

0.2628

y ̂ = 2.53083 + 0.18833 *xl* -0.16917 *xW* + 0.11139 *xWxd* + 0.08194 *xWxF* + 0.05694 *xwxW*

R-code for Hamadu Wu method for dispersion –

**Step1**

# For Dispersion Effects  
  
#for factor l  
m1 = lm(lns2~l+lw+lL+lW+ld+lF ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m1)

##   
## Stepwise Selection Summary   
## ------------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## ------------------------------------------------------------------------------------  
## 1 lw addition 0.123 0.036 -1.6810 38.9669 1.0469   
## ------------------------------------------------------------------------------------

# for factor w  
m2 = lm(lns2~w+wL+wW+wd+wF+lw ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m2)

##   
## Stepwise Selection Summary   
## ------------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## ------------------------------------------------------------------------------------  
## 1 wL addition 0.474 0.421 17.7650 32.8345 0.8108   
## 2 w addition 0.684 0.614 9.4820 28.7229 0.6626   
## 3 lw addition 0.807 0.735 5.4480 24.7962 0.5490   
## ------------------------------------------------------------------------------------

# for factor L  
m3 = lm(lns2~L+LW+Ld+LF+wL+lL ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m3)

##   
## Stepwise Selection Summary   
## ------------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## ------------------------------------------------------------------------------------  
## 1 wL addition 0.474 0.421 13.9700 32.8345 0.8108   
## 2 LW addition 0.821 0.781 1.4930 21.9269 0.4992   
## ------------------------------------------------------------------------------------

# for factor W  
m4 = lm(lns2~W+Wd+WF+LW+wW+lW ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m4)

##   
## Stepwise Selection Summary   
## -----------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## -----------------------------------------------------------------------------------  
## 1 LW addition 0.347 0.281 4.5030 35.4380 0.9038   
## 2 Wd addition 0.566 0.469 2.3060 32.5296 0.7764   
## -----------------------------------------------------------------------------------

# for factor d  
m5 = lm(lns2~d+dF+Wd+Ld+wd+ld ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m5)

##   
## Stepwise Selection Summary   
## -----------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## -----------------------------------------------------------------------------------  
## 1 dF addition 0.283 0.211 9.7260 36.5501 0.9466   
## 2 Wd addition 0.502 0.392 6.3020 34.1668 0.8313   
## -----------------------------------------------------------------------------------

# for factor F  
m6 = lm(lns2~F+dF+WF+LF+wF+lF ,data=df) # Using stepwise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m6)

##   
## Stepwise Selection Summary   
## ------------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## ------------------------------------------------------------------------------------  
## 1 dF addition 0.283 0.211 -0.3430 36.5501 0.9466   
## ------------------------------------------------------------------------------------

By performing Step 1 we get the following significant main effects and interaction effects for Dispersion: w,wL,LW,lw,Wd,dF We consider this interaction effects along with all the main effects for performing step2

**Step2**

#Step 2  
#Considering all significant factors obtained from step1  
m7 = lm(lns2~ l+w+L+W+F+d+lw+wL+LW+Wd+dF ,data=df) # Using step wise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m7)

##   
## Stepwise Selection Summary   
## ---------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## ---------------------------------------------------------------------------------  
## 1 wL addition 0.474 0.421 NaN 32.8345 0.8108   
## 2 LW addition 0.821 0.781 NaN 21.9269 0.4992   
## 3 w addition 0.898 0.859 NaN 17.1773 0.3997   
## 4 lw addition 0.938 0.902 NaN 13.1867 0.3329   
## ---------------------------------------------------------------------------------

We obtain main effect w and interaction effects wL,LW,lw as the significant factors by performing step 2. We consider all the main effects and interaction effects whose atleast 1 component main effect is significant as obtained from step 2 for performing step 3.

**Step3**

#Step 3  
#Considering all significant factors obtained from step2  
m8 = lm(lns2~ w+wW+wL+wd+wF+lw ,data=df) # Using step wise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m8)

##   
## Stepwise Selection Summary   
## ------------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## ------------------------------------------------------------------------------------  
## 1 wL addition 0.474 0.421 17.7650 32.8345 0.8108   
## 2 w addition 0.684 0.614 9.4820 28.7229 0.6626   
## 3 lw addition 0.807 0.735 5.4480 24.7962 0.5490   
## ------------------------------------------------------------------------------------

By performing Step 3 as above we get main effects w as significant. While we obtain wL,lw as significant interaction effects. Here we perform step 4 by repeating step 2 and 3 untill we obtain the same model as obtained from previous step.

**Step4**

#Step 4   
#Considering all significant factors obtained from step1  
m9 = lm(lns2~l+w+L+W+F+d+lw+wL ,data=df) # Using step wise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m9)

##   
## Stepwise Selection Summary   
## ------------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## ------------------------------------------------------------------------------------  
## 1 wL addition 0.474 0.421 17.4230 32.8345 0.8108   
## 2 w addition 0.684 0.614 9.2770 28.7229 0.6626   
## 3 lw addition 0.807 0.735 5.3230 24.7962 0.5490   
## 4 d addition 0.883 0.815 3.6780 20.8465 0.4580   
## 5 W addition 0.930 0.871 3.3890 16.6536 0.3822   
## ------------------------------------------------------------------------------------

**Step5 & Step6**

#Step 5  
#Considering all significant factors obtained from step2  
m10 = lm(lns2~ W+w+d+Wd+WF+LW+wW+lW+dF+Ld+wd+ld+wL+wF+lw ,data=df) # Using step wise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m10)

##   
## Stepwise Selection Summary   
## ---------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## ---------------------------------------------------------------------------------  
## 1 wL addition 0.474 0.421 NaN 32.8345 0.8108   
## 2 LW addition 0.821 0.781 NaN 21.9269 0.4992   
## 3 w addition 0.898 0.859 NaN 17.1773 0.3997   
## 4 lw addition 0.938 0.902 NaN 13.1867 0.3329   
## ---------------------------------------------------------------------------------

#Step 6   
#Considering all significant factors obtained from step1  
m11 = lm(lns2~l+w+L+W+F+d+wL+LW+lw ,data=df) # Using step wise method by adding and deleting factors to determine the optimum solution  
ols\_step\_both\_p(m11)

##   
## Stepwise Selection Summary   
## ------------------------------------------------------------------------------------  
## Added/ Adj.   
## Step Variable Removed R-Square R-Square C(p) AIC RMSE   
## ------------------------------------------------------------------------------------  
## 1 wL addition 0.474 0.421 30.3300 32.8345 0.8108   
## 2 LW addition 0.821 0.781 7.0740 21.9269 0.4992   
## 3 w addition 0.898 0.859 3.4490 17.1773 0.3997   
## 4 lw addition 0.938 0.902 2.5220 13.1867 0.3329   
## ------------------------------------------------------------------------------------

Thus we obtain same model by step 5 and step 6, so we stop at step 6 and we obtain the significant factors as w,lw,LW,wL for Dispersion. We obtain an adjusted R^2 as 90.2%

lns2 = -4.0088 + 0.3281 *xw* - 0.7027 *xwxL* - 0.4186 *xWxL* + 0.2187 *xlxw*

**4. Analysis for Hamada Wu method –**

In order to increase the flight time of paper helicopter we reduce the variance of the design by considering the following setting of the factors as obtained from the dispersion effect analysis.

lns2 = -4.0088 + 0.3281 *xw* - 0.7027 *xwxL* - 0.4186 *xWxL* + 0.2187 *xlxw*

We can see from the equation above that to reduce the variance we set the factors as below,

Wing width(w) at the (-) level at 1.8 inches.

Body length (L) at the (-) level which is at 3 inches.

Body width(W) at the (-) level too which is 1.25 inches.

Wing length(l) at (+) level which is at 4.5 inches.

We consider the above setting for reducing the variance and determining the following value of variance:

lns2 = -4.0088 + 0.3281 *xw* - 0.7027 *xwxL* - 0.4186 *xWxL* + 0.2187 *xlxw*

lns2 = -4.0088 + 0.3281(-1) - 0.7027(-1)(-1) - 0.4186(-1)(-1) + 0.2187(+1)(-1)

lns2 = -5.6769

Thus, using the above setting obtained from dispersion effects we determine the flight time for paper helicopter as,

y ̂ = 2.53083 + 0.18833 *xl* -0.16917 *xW* + 0.11139 *xWxd* + 0.08194 *xWxF* + 0.05694 *xwxW*

y ̂ = 2.53083 + 0.18833(+1) - 0.16917(-1) + 0.11139(-1)d + 0.08194(-1)F + 0.05694(-1)(-1)

In order to obtain the maximum flight time, we consider various combinations for d and F as (+,+), (-,-), (+,-), (-,+) and select the one which gives us the maximum flight time for the paper helicopter.

We select the (-,-) d(1 inch) and F(no fold at tip) for which we get the maximum flight time value

y ̂ = 3.138 seconds.

**Validation:**

We need to craft a paper helicopter with the settings identified by Hamada Wu analysis for maximizing flight time.

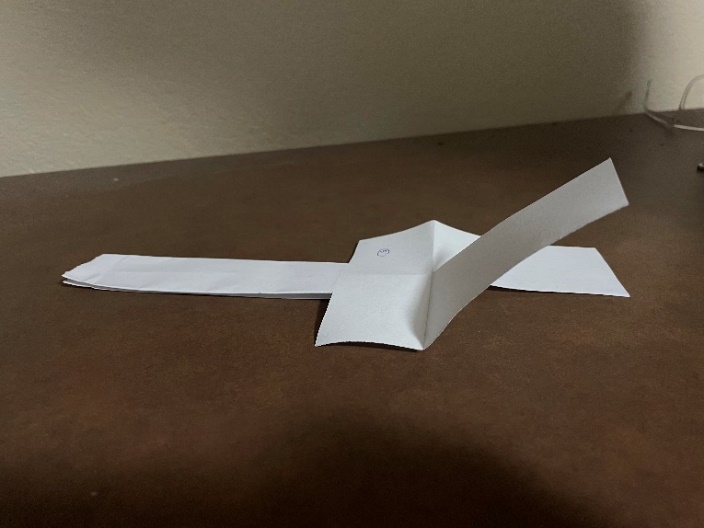
Following optimal settings for factors are identified from Hamada Wu analysis –

*Table 5:*- Optimal Structural dimensions identified by Hamada Wu analysis for Crafting the Paper Helicopter

|  |  |  |
| --- | --- | --- |
| Factors | Symbol | Dimensions |
| Wing length | l | 4.5 inches |
| Wing width | w | 1.8 inches |
| Body length | L | 3 inches |
| Middle body length | d | 1 inch |
| Fold at tip | F | no |
| Body Width | W | 1.25 inches |

Crafting a paper helicopter with the above dimensions,

**Photo of Validation Paper Helicopter**

****

By designing the paper helicopter for validation as above for the above recommended optimal setting we obtain the flight time as **3.07** seconds, which is much closer to the value obtained by theoretical calculation as above which is **3.138** seconds.

**Conclusion:**

The Experiment of Paper Helicopter was performed to increase the flight time of the paper helicopter for which experiment was designed using **Plackett-Burman** design OA(12,26).

The paper helicopters were crafted as explained in the procedure above, and the data was recorded considering only the factors mentioned above, and ignoring the other factors that might affect the experiment such as wind, human error…

Initially, the significant factors were identified by **Half-Normal** plot approach. The significant factors were identified by this approach and the maximum flight time calculated by half-normal plot is **2.8792** seconds.

Then Hamada Wu analysis was performed, and the significant factors were identified and the maximum flight time calculated by **Hamada Wu** analysis is **3.138** seconds.

Thus, from the above analysis we can confirm that Hamada Wu strategy provides significant main effect as well as interaction effects, and in order to increase the flight time we design the paper helicopter according to the optimal setting obtained above.

The optimal setting for maximizing flight time were identified and the model was validated.

An increase of **8.9%** in flight time is observed using Hamada Wu analysis over the half normal plot analysis.