Laptop Battery Efficiency: Evaluating Key Influences

Statistics 453 Final Project

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1 Introduction

Nowadays it is very common for people to have laptops for personal, academic, or professional settings. The main feature of a laptop is its portability, allowing users to carry out tasks in a multitude of environments. However, battery life is a significant concern for laptop users, as it dictates the usability of their devices. Identifying how factors such as screen brightness, active processes, Bluetooth connectivity, and power settings contribute to battery drain is crucial for enhancing energy management and extending laptop usage between charges. This study will assess the impact of these factors on battery longevity and focus on how battery life can be optimized for diverse usage scenarios.

Performing a 2^4 factorial design, the factors and their interactions can be analyzed and their effect on laptop depletion rate can be tested. The data will be collected using 3 different laptops, serving as replicates (blocks) in the study, The operating system of the laptops will serve as additional blocks for this study.

2 Design of the Experiment

2.1 Design

The study design will be a 2^4 factorial design experiment to explore the impact of four key factors on laptop battery depletion rate. These factors are:

- Screen Brightness (A) with two levels: low (-), high (+).
- Active Processes (B) with two levels: moderate usage (-), heavy usage (+).
- Bluetooth Enabled (C) with two levels: off (-), on (+)
- Battery Saving Mode (D) with two levels: on (-), off (+).

The levels for each factor are defined as follows: Low screen brightness (-) indicates 50% of the full brightness capacity. High screen brightness (+) indicates 80% of the full brightness capacity. For active processes, moderate usage (-) is any three light productivity software applications. For this study, we define it as a web browser with two tabs open and a word processor for three total processes. Heavy usage (+) includes running multiple applications simultaneously. In this experiment, we define it as follows: A web browser streaming a video on YouTube, playing a flash game (in this experiment we chose the flash game Bubble Shooter), and 2 additional tabs. Additionally, a word processing application would be open, and another application would be playing music (in this experiment we chose Spotify). This is a total of six processes.

This experiment will have three replicates. Each replicate will collect data for all 16 combinations of factors for a total of 48 runs. Each run will have the laptop operate for 10 minutes. 10 minutes was chosen as we are more interested in the immediate effects of various settings on battery depletion rate. It is also a practical amount of time to collect initial data on the topic without being overly time consuming.

2.2 Nuisance Factors

There are both uncontrollable and controllable nuisance factors involved in this study. Uncontrollable nuisance factors include characteristics of the laptop hardware itself. Laptop brand, age, overall battery health, background processes, and operating system cannot be easily changed. We decided to block by both laptop and operating system to control for these factors. The controllable nuisance factors involve the software used during the test procedure. For example, two different music players could have different impact on battery depletion. To account for this, we used as similar a program as possible across replicates (ie all replicates used Spotify as the music player.

2.3 Three Basic Principles

In this experimental design, we adhere to three fundamental principles to ensure the integrity and reliability of our findings. Replication is achieved by repeating each combination of the factorial design three times on three different laptops. Randomization is achieved as we assign the different combinations of factors to our test laptops in a random sequence. Blocking is achieved by replication as previously mentioned. Additionally, we also block by operating system. These blocks aim to control various nuisance factors.

2.4 Statistical Model

The experiment will be analyzed using an ANOVA (Analysis of Variance) to test for the main effects and interactions of the factors on battery life. The model will include terms for blocks, factors, and their interactions.

The initial statistical model for this experiment is:

$$\begin{aligned} Y_{ijklmno} = {} & \mu + \tau_i + \beta_j + (\tau\beta)_{ij} + \gamma_k + (\tau\gamma)_{ik} + (\beta\gamma)_{jk} + (\tau\beta\gamma)_{ijk} + \lambda_l + (\tau\lambda)_{il} + (\beta\lambda)_{jl} \\ & + (\gamma\lambda)_{kl} + (\tau\beta\lambda)_{ijl} + (\tau\gamma\lambda)_{ikl} + (\beta\gamma\lambda)_{jkl} + (\tau\beta\gamma\lambda)_{ijkl} + \delta_n + \varphi_o \\ & + \epsilon_{ijklmno} \end{aligned}$$

for $i = 1, 2$; $j = 1, 2$; $k = 1, 2$; $l = 1, 2$; $n = 1, 2, 3$; $o = 1, 2$; where: $Y_{ijklmno}$ is the observed battery depletion rate; μ is the overall mean depletion rate; τ_i is the effect of i^{th} level of factor A (screen brightness); β_j is the effect of j^{th} level of factor B (active processes); γ_k is the effect of k^{th} level of factor C (Bluetooth connectivity); λ_l is the effect of l^{th} level of factor D (battery saving mode), $(\tau\gamma)_{ik}$,$(\beta\gamma)_{jk}$, … represent the interaction effects between the factors; δ_n, φ_o are the blocks, and $\epsilon_{ijklmno}$ is the random error term, where $\epsilon_{ijklmno} \sim N(0, \sigma^2)$.

This model assumes that the random error is normal with constant variance. We also assume based on prior experience that laptop battery drain occurs at different rates depending on the battery's current percentage. This is accounted for in the experimental procedure.

3 Experimental Procedure and Data Collection

To assess the impact of screen brightness, active processes, Bluetooth connectivity, and battery saving mode on laptop battery life, we set the following procedure. For each replicate, randomize the run order to ensure that randomization is achieved in the study. Close all irrelevant programs and background processes. Then for each run:

1. Charge the laptop as close to 70% as possible and record the starting battery percentage.
2. Setup and adjust the factors as necessary to match the current run.
3. Unplug and allow the laptop to operate for 10 minutes.
4. Record the final battery percentage and calculate the change in battery percentage.

Anecdotal experiences among group members indicated that laptop batteries seem to drain slowly when near full (>90%) but quickly when near empty (<20%). As a result, 70% was chosen as the initial battery percentage. We felt that 70% was far enough away from a full charge so that it was more representative of a standard battery drain, but not so low that the experiment could cause a laptop to enter forced battery saver mode. Choosing 70% as a starting percentage also introduces consistency in the model design.

The data from the experiment is displayed in the following table:

Factors					Change in %		
Run Label	A: Brightness	B: Processes	C: Bluetooth	D: Battery Mode	I Mac	II Windows	III Mac
(1)	-	-	-	-	1	1	1
a	+	-	-	-	3	1	7
b	-	+	-	-	7	4	6
ab	+	+	-	-	6	4	10
c	-	-	+	-	2	1	4
ac	+	-	+	-	3	2	5
bc	-	+	+	-	6	4	3
abc	+	+	+	-	6	5	12
d	-	-	-	+	3	2	6
ad	+	-	-	+	3	2	1
bd	-	+	-	+	8	5	5
abd	+	+	-	+	10	6	5
cd	-	-	+	+	4	2	5
acd	+	-	+	+	4	3	7
bcd	-	+	+	+	7	5	6
abcd	+	+	+	+	12	7	12

Table 1: Factors and Collected Data

4 Data Analysis

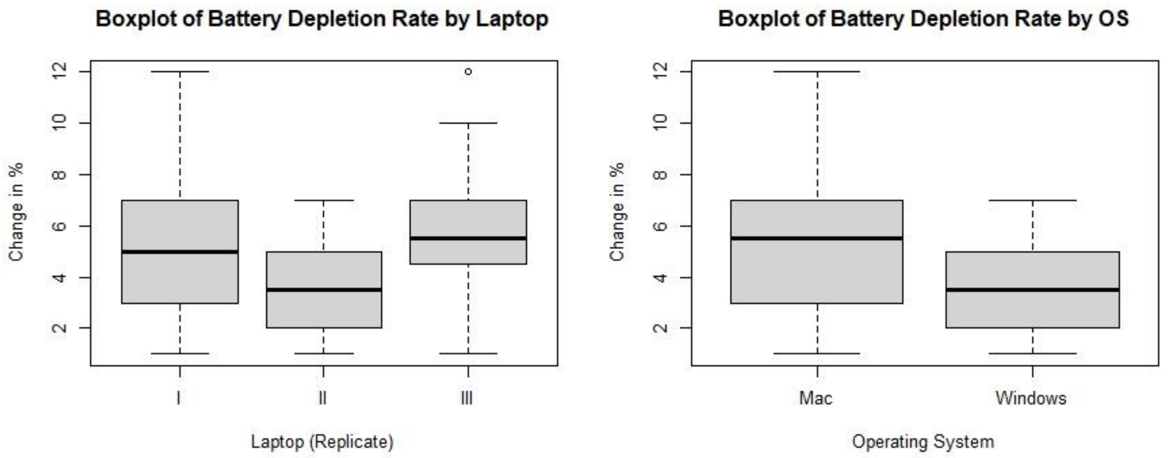

Figure 1: Boxplot of Battery Depletion by Blocks

The boxplots of battery consumption separated by block help to visualize the data while minimizing the nuisance factors. We can see that the boxplots blocked by OS are significantly different visually. It is difficult to determine whether the boxplots blocked by laptop have significant differences.

4.1 Model Adequacy

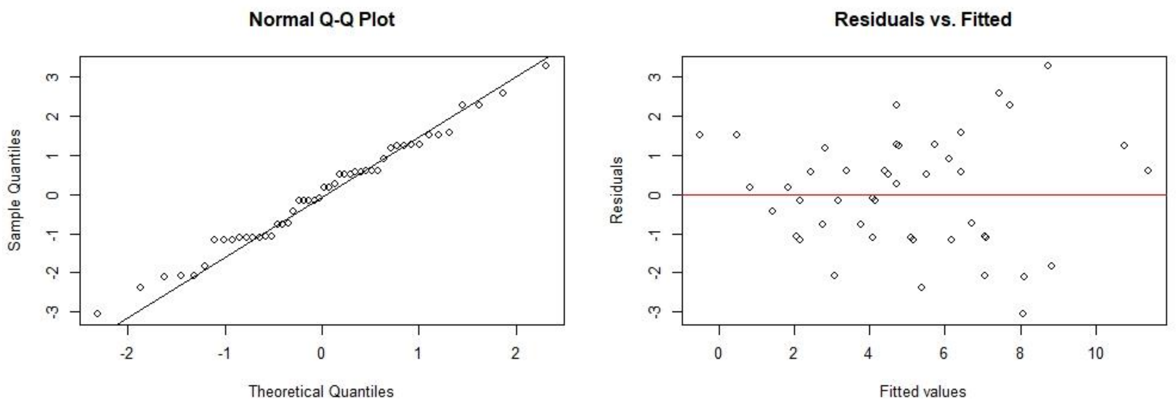

Figure 2: Model Adequacy Plots

To check model adequacy, we check the assumptions that: the data is normal, and the variance is constant. The Normal Q-Q plot of residuals seem to have some pattern, but mostly lie on the diagonal. Furthermore, the Shapiro-Wilk test in R gives a p-value of $p = .8127$, indicating that there is no evidence against the hypothesis that the data is normal. The normality assumption is satisfied. The Residual vs Fitted plot shows no obvious pattern. While there may be a slight bell-shape in the plot, it is not strong enough to indicate that the variance is not constant. Thus, the constant variance assumption is also satisfied.

4.2 Interaction Plots

The interaction plots are separated by block to minimize bias from potential nuisance factors.

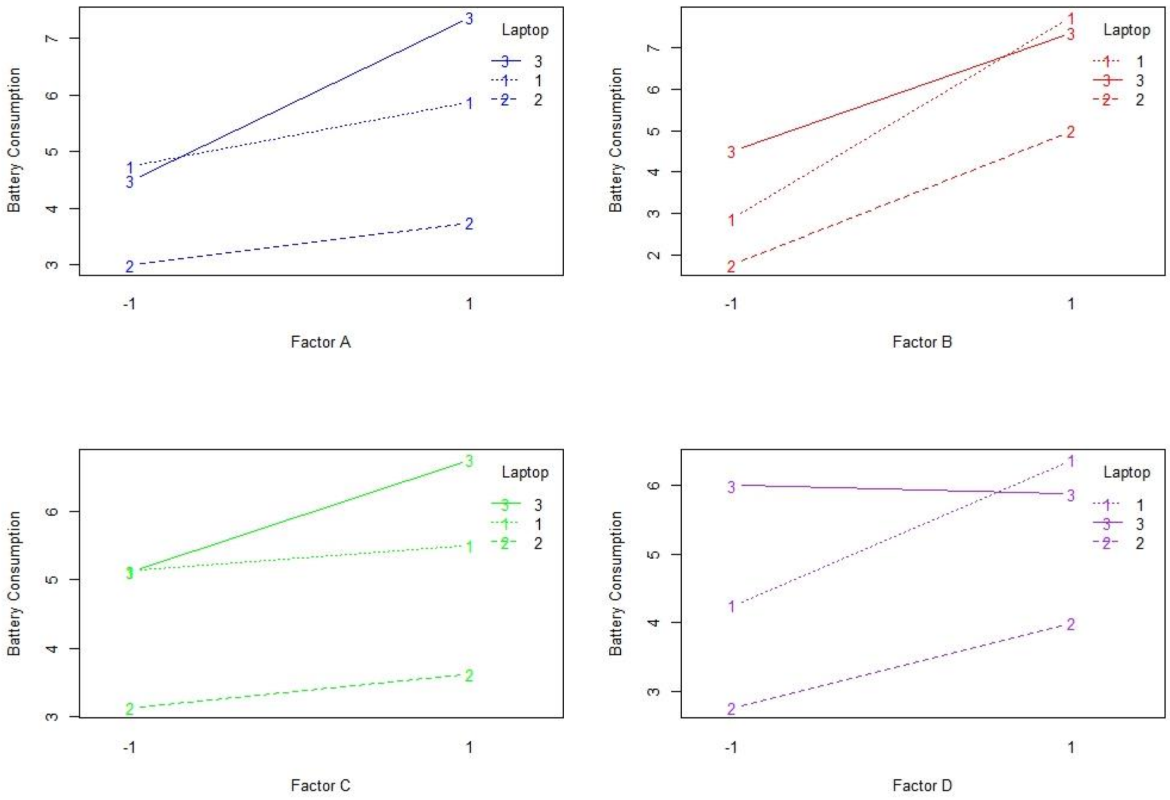

Figure 3: Main Effect Interaction Plots by Laptop

Each laptop showed an increase in battery consumption when changing from the low level (-) to the high level (+). The exception is in the third replicate for factor D: battery saving mode. It seem to slightly decrease in battery consumption after turning batter saver mode off (+). Given the use case of battery saving mode, we believe this to be measurement error that was not noticed until the data collection was complete. The wording of the levels may have attributed to this result since batter saver mode on is the low level (-). Given the time constraint it was not possible to recollect the data.

In general, Laptop 3 seemed to show more aggressive changes compared to the other two replicates. Only in Factor B: processes do the three replicates have similar slopes. Laptop 2 also had much lower average battery consumption. This is believed to be due to the OS differing from both Laptop 1 and 3, which can be seen in Figure 4.

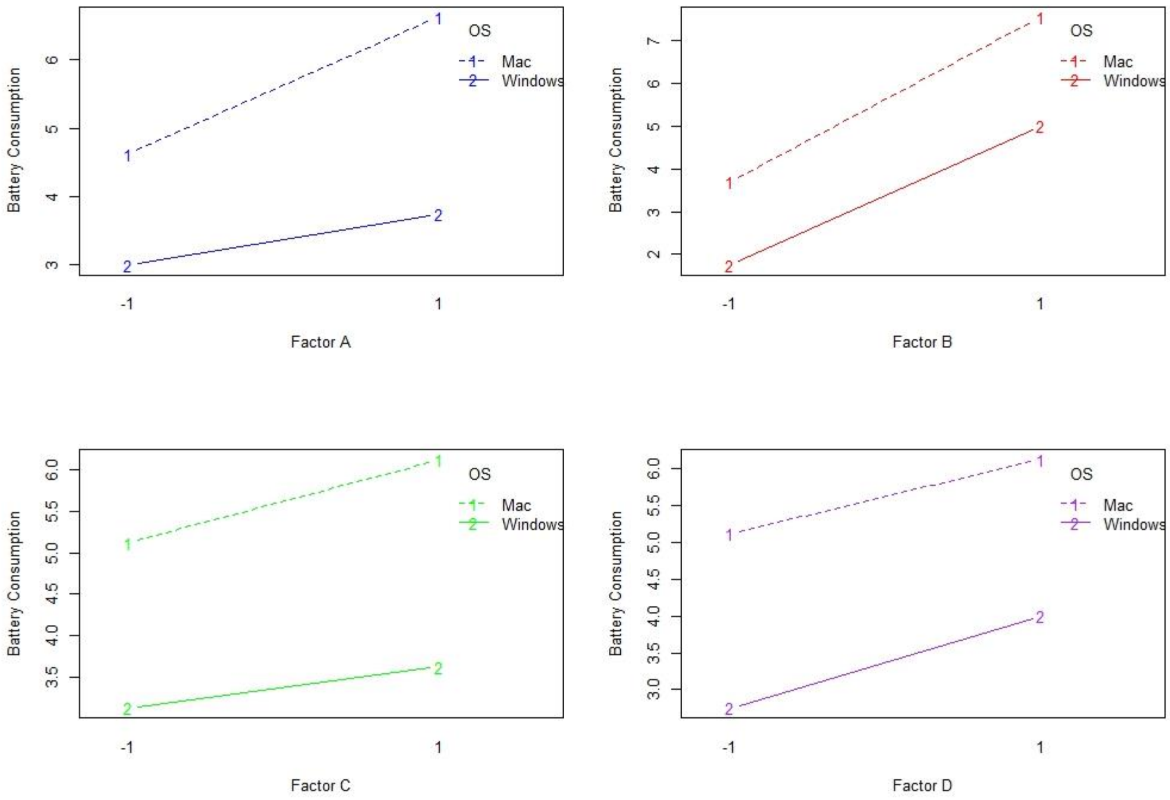

Figure 4: Main Effect Interaction Plots by OS

When separating by OS, we see major difference in the overall magnitude on the y-axis of each interaction plot. This indicates that there is possibly a significant difference in how the operating systems handle battery consumption.

4.3 ANOVA

Using R, we obtain the following ANOVA table:

```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## A             1  30.08   30.08  10.005 0.003562 **
## B             1 161.33  161.33  53.654  3.7e-08 ***
## C             1   8.33    8.33   2.771 0.106376
## D             1  14.08   14.08   4.684 0.038540 *
## laptop        1   3.12    3.12   1.039 0.316145
## os            1  54.00   54.00  17.958 0.000198 ***
## A:B           1   8.33    8.33   2.771 0.106376
## A:C           1   8.33    8.33   2.771 0.106376
## B:C           1   0.08    0.08   0.028 0.868901
## A:D           1   2.08    2.08   0.693 0.411777
## B:D           1   0.33    0.33   0.111 0.741489
## C:D           1   5.33    5.33   1.774 0.192959
## A:B:C         1   4.08    4.08   1.358 0.253072
## A:B:D         1   5.33    5.33   1.774 0.192959
## A:C:D         1   5.33    5.33   1.774 0.192959
## B:C:D         1   0.75    0.75   0.249 0.621125
## A:B:C:D       1   2.08    2.08   0.693 0.411777
## Residuals    30  90.21    3.01
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 5: ANOVA Table for Initial Model

In the initial model, the only significant effects are the main effects A, B, and D, as well as the effect from blocking by OS. We obtain the final model by removing the insignificant terms with the highest p-value starting with the highest order interaction terms. The resulting final model is obtained in R is shown in Figure 6.

```
##             Df Sum Sq Mean Sq F value   Pr(>F)    
## A            1  30.08   30.08   8.999 0.004481 ** 
## B            1 161.33  161.33  48.260 1.54e-08 ***
## D            1  14.08   14.08   4.213 0.046239 *  
## os           1  54.00   54.00  16.153 0.000231 ***
## Residuals   43 143.75    3.34                     
## ---
```

Figure 6: ANOVA Table for Final Model

In the final model, the included effects are the same as the significant effects in the initial model. That is, main effects A: Brightness, B: Processes, and D: Power Saving Mode as well as the effect from blocking by OS remain.

5 Conclusion and Recommendation

The goal of the study was to determine which factors which can cause battery consumption to increase. The factors that were chosen were as such due them being more controllable (eg. Wi-Fi is usually non-negotiable when using a laptop for most tasks but factors such as screen brightness or Bluetooth can usually be switched on or off in any use-case). The ANOVA analysis showed that the factors screen brightness, process usage, and power saving mode all had significant impact on increasing battery consumption. Bluetooth was a negligible factor, as was all interaction terms. Furthermore, there was no indication that background processes, laptop age, or battery health has any large consequences on battery consumption as the laptop block (replication) effect was not significant. On the other hand, operating systems can make a large difference in battery consumption as shown by its block effect.

The process usage factor affected battery consumption the strongest, as seen in the interaction plots (Fig. 3 and Fig. 4) by its steeper slopes and higher average battery consumption. This is also shown in the final model ANOVA table, as it has the highest p-value. Thus, we recommend minimizing processes as much as possible to maximize uptime. Lowering screen brightness and turning on power saver mode also have significant effects on saving battery life.

5.1 Further Study

Many factors were not able to be properly assessed in this study. One such factor is the usage of any peripherals. Many individuals use USB devices such as mice or keyboards when using laptops. Also, as operating systems were found to have significant impact on battery consumption, an adjacent experiment can be carried out comparing different OS's such as Windows, Mac, and Linux to determine which operating system is best suited for power users.

6 Appendix

6.1 R Code

```
library("daewr")

## Warning: package 'daewr' was built under R version 4.2.3

# Initialize data
battery <- c(1, 3, 7, 6, 2, 3, 6, 6, 3, 3, 8, 10, 4, 4, 7, 12,  # Replicate
1
             1, 1, 4, 4, 1, 2, 4, 5, 2, 2, 5, 6, 2, 3, 5, 7,    # Replicate 2
             1, 7, 6, 10, 4, 5, 3, 12, 6, 1, 5, 5, 5, 7, 6, 12) # Replicate 3
A <- c(rep(rep(rep(c(-1,1)),8),3))                              # Brightness
B <- c(rep(rep(c(rep(-1,2),rep(1,2)),4),3))                      # Processes
C <- c(rep(rep(c(rep(-1,4),rep(1,4)),2),3))                      # Bluetooth
D <- c(rep(c(rep(-1,8),rep(1,8)),3))                            # Power Mode
laptop <- c(rep(1,16),rep(2,16),rep(3,16))                       # Block 1
os <- c(rep("Mac", 16), rep("Windows", 16), rep("Mac",16))        # Block 2
df <- data.frame(A,B,C,D,laptop,os)

# Graph boxplots by block to visualize df
par(mfrow = c(2, 2))
boxplot(battery[1:16], battery[17:32], battery[33:48],          # By laptop
        names = c("I", "II", "III"),
        xlab = "Laptop (Replicate)",
        ylab = "Change in %",
        main = "Boxplot of Battery Depletion Rate by Laptop")

boxplot(c(battery[1:16], battery[33:48]), battery[17:32],       # By OS
        names = c("Mac", "Windows"),
        xlab = "Operating System",
        ylab = "Change in %",
        main = "Boxplot of Battery Depletion Rate by OS")

# Graph boxplots of main factors
# boxplot(battery[df$A==1],battery[df$B==1],battery[df$C==1],battery[df$D=
=1],
#         names = c("A: Brightness", "B: Processes","c: Bluetooth","D: Power
 Saving Mode"),
#         xlab = "Factor",
#         ylab = "Battery Consumption")
```

```r
# Graph interaction plots by blocks
par(mfrow = c(2, 2))

# Interaction plots by laptop block
interaction.plot(df$A, df$laptop, battery, # Brightness
                type = "b",
                col = "blue",
                xlab = "Factor A",
                ylab = "Battery Consumption",
                trace.label = "Laptop")
interaction.plot(df$B, df$laptop, battery, # Processes
                type = "b",
                col = "red",
                xlab = "Factor B",
                ylab = "Battery Consumption",
                trace.label = "Laptop")
interaction.plot(df$C, df$laptop, battery, # Bluetooth
                type = "b",
                col = "green",
                xlab = "Factor C",
                ylab = "Battery Consumption",
                trace.label = "Laptop")
interaction.plot(df$D, df$laptop, battery, # Power mode
                type = "b",
                col = "purple",
                xlab = "Factor D",
                ylab = "Battery Consumption",
                trace.label = "Laptop")

# Interaction plots by OS block
par(mfrow = c(2, 2))
interaction.plot(df$A, df$os, battery,     # Brightness
                type = "b",
                col = "blue",
                xlab = "Factor A",
                ylab = "Battery Consumption",
                trace.label = "OS")
interaction.plot(df$B, df$os, battery,     # Processes
                type = "b",
                col = "red",
                xlab = "Factor B",
                ylab = "Battery Consumption",
                trace.label = "OS")
interaction.plot(df$C, df$os, battery,     # Bluetooth
```

```
                 type = "b",
                 col = "green",
                 xlab = "Factor C",
                 ylab = "Battery Consumption",
                 trace.label = "OS")
interaction.plot(df$D, df$os, battery,     # Power mode
                 type = "b",
                 col = "purple",
                 xlab = "Factor D",
                 ylab = "Battery Consumption",
                 trace.label = "OS")

# Fit a linear model
res.lm <- lm(battery~A*B*C*D+(laptop+os),
             data = df)
summary(res.lm)
```

```
##
## Call:
## lm(formula = battery ~ A * B * C * D + (laptop + os), data = df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.0625 -1.1042  0.0313  0.9635  3.2708
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.00000    0.68545   7.295 4.01e-08 ***
## A            0.79167    0.25029   3.163 0.003562 **
## B            1.83333    0.25029   7.325 3.70e-08 ***
## C            0.41667    0.25029   1.665 0.106376
## D            0.54167    0.25029   2.164 0.038540 *
## laptop       0.31250    0.30654   1.019 0.316145
## osWindows   -2.25000    0.53094  -4.238 0.000198 ***
## A:B          0.41667    0.25029   1.665 0.106376
## A:C          0.41667    0.25029   1.665 0.106376
## B:C         -0.04167    0.25029  -0.166 0.868901
## A:D         -0.20833    0.25029  -0.832 0.411777
## B:D          0.08333    0.25029   0.333 0.741489
## C:D          0.33333    0.25029   1.332 0.192959
## A:B:C        0.29167    0.25029   1.165 0.253072
## A:B:D        0.33333    0.25029   1.332 0.192959
## A:C:D        0.33333    0.25029   1.332 0.192959
## B:C:D        0.12500    0.25029   0.499 0.621125
```

```
## A:B:C:D     -0.20833    0.25029  -0.832 0.411777
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.734 on 30 degrees of freedom
## Multiple R-squared:  0.7763, Adjusted R-squared:  0.6495
## F-statistic: 6.124 on 17 and 30 DF,  p-value: 8.853e-06
```

```
# ANOVA
res.aov <- aov(battery~A*B*C*D+(laptop+os),
              data = df)
summary(res.aov)
```

```
##             Df Sum Sq Mean Sq F value   Pr(>F)
## A            1  30.08   30.08  10.005 0.003562 **
## B            1 161.33  161.33  53.654  3.7e-08 ***
## C            1   8.33    8.33   2.771 0.106376
## D            1  14.08   14.08   4.684 0.038540 *
## laptop       1   3.12    3.12   1.039 0.316145
## os           1  54.00   54.00  17.958 0.000198 ***
## A:B          1   8.33    8.33   2.771 0.106376
## A:C          1   8.33    8.33   2.771 0.106376
## B:C          1   0.08    0.08   0.028 0.868901
## A:D          1   2.08    2.08   0.693 0.411777
## B:D          1   0.33    0.33   0.111 0.741489
## C:D          1   5.33    5.33   1.774 0.192959
## A:B:C        1   4.08    4.08   1.358 0.253072
## A:B:D        1   5.33    5.33   1.774 0.192959
## A:C:D        1   5.33    5.33   1.774 0.192959
## B:C:D        1   0.75    0.75   0.249 0.621125
## A:B:C:D      1   2.08    2.08   0.693 0.411777
## Residuals   30  90.21    3.01
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# For model adequacy checking
res <- res.lm$residuals

# Check for normality
qqnorm(res)
qqline(res)
shapiro.test(res)
```

```
##
##  Shapiro-Wilk normality test
```

```
##
## data:  res
## W = 0.98554, p-value = 0.8127
```

```
# Check for constant variance
plot(res.lm$fitted.values, res, xlab = "Fitted values", ylab = "Residuals",
 main = "Residuals vs. Fitted")
abline(h = 0, col = "red")

# Fullnormal plot
# fullnormal(na.omit(coef(res.lm)[-1]),alpha = .005)

# Drop interaction terms by highest p-value to obtain final model

# Final model
res.aov.final <- update(res13.aov,~.-C)
summary(res.aov.final)
```

```
##             Df Sum Sq Mean Sq F value   Pr(>F)
## A            1  30.08   30.08   8.999 0.004481 **
## B            1 161.33  161.33  48.260 1.54e-08 ***
## D            1  14.08   14.08   4.213 0.046239 *
## os           1  54.00   54.00  16.153 0.000231 ***
## Residuals   43 143.75    3.34
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Note: The code for dropping of insignificant terms in the model was omitted due to being very lengthy.

7 References

Montgomery, D. C. (2017). *Design and Analysis of Experiments* (10th ed.). Wiley.