ENHANCING EFFICIENCY OF POTATO BATTERIES: A SUSTAINABLE ENERGY SOLUTION

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Introduction

Access to affordable and sustainable energy is crucial for improving the lives of billions of people worldwide who lack reliable electrical infrastructure. Inspired by previous research exploring the potential of potato-based batteries to generate electricity, our project aims to further investigate and optimize this simple and accessible energy solution.

In 2010, Golberg, Rabinowitch, and Rubinsky demonstrated that treated potato tissues could produce significantly more electric power compared to untreated ones. This discovery hinted at the possibility of using potatoes as a cost-effective energy source for communities without access to traditional power grids.

Building upon this prior work, our project introduced another factor: the type of potato based on their starchiness. This additional factor was included to further contribute to the understanding of potato battery efficiency.

Potatoes are one of the most commonly found crops around the world, and leveraging them as a source of electricity could offer a sustainable solution for powering low-energy tools such as LED lights or charging cellphones. In this study, we utilized a 2^3 factorial design with interactions to investigate this matter. The experiment was conducted with two replicates to ensure the reliability of our findings.

Design of Experiment

In our experiment, we employed a 2^3 factorial design to investigate the efficiency of potato batteries. This design allowed us to systematically vary three factors: the type of potato, boiling condition, and state of the potato. We chose Yukon Gold (waxy) and Russet (starchy) potatoes to represent different levels of starch content, aiming to discern their impact on battery performance. Additionally, we examined the effect of boiling the potatoes versus using them unboiled, hypothesizing that the breakdown of cell membranes during boiling could affect electrical power generation. Furthermore, we explored the state of the potato, whether it was used as a whole or quartered and wired in parallel, to observe the influence of contact area on battery efficiency.
The response factor in our experiment is power, measured in watts (W), which is a critical indicator of the efficiency and performance of the potato batteries. Power is calculated by multiplying the voltage and amperage generated by the potato battery. Voltage represents the electrical potential difference between the two electrodes, while amperage indicates the flow of electric current through the circuit. By multiplying these two values, we obtain the power output of the potato battery, which directly reflects its ability to convert chemical energy stored within the potato into electrical energy. Monitoring power output allows us to quantify the effectiveness of different experimental conditions, such as varying potato types and boiling conditions, in maximizing energy production. Ultimately, optimizing power output is essential for enhancing the practical utility and viability of potato batteries as sustainable energy sources for various applications.

To address nuisance factors, we incorporated a block effect for each replicate to account for variations in cooling time after boiling. Additionally, we minimized the influence of environmental conditions through randomization of run orders, ensuring that unknown variables such as room temperature were evenly distributed across experimental runs.

Our experimental design adhered to the three basic principles of experimental design: randomization, replication, and blocking. Randomization of run orders was implemented to mitigate the effects of unknown variables, while replication of each combination of factor levels was conducted twice to enhance the reliability of our findings. Furthermore, we introduced blocking for each replicate to control for nuisance factors such as variations in cooling time after boiling.

The statistical model used to analyze our experiment is expressed as follows:

$$\begin{aligned} Watts = \beta_0 + \beta_1 Potato + \beta_2 Boiled + \beta_3 State + \beta_4 Relicate + \beta_{12} Potato\!:\!Boiled \\ + \beta_{13} Potato\!:\!State + \beta_{23} Boiled\!:\!State + \beta_{123} Potato\!:\!Boiled\!:\!State \end{aligned}$$

Here, Watts represents the observed response variable (electrical power), while $\beta_0, \beta_1, \beta_3, \beta_4, \beta_{12}, \beta_{13}, \beta_{23}, and\ \beta_{123}$ are the coefficients representing the effects of the respective factors and their interactions. This model allows us to assess the individual and combined effects of the factors on potato battery efficiency, providing valuable insights into optimizing their performance for practical applications.

Data Collection

Our experiment was conducted in the staff lounge with meticulous attention to detail to ensure consistency and reliability in data collection. Three team members were present, each assigned specific roles to streamline the experimental process. Prior to the experiment, we procured potatoes of approximately the same age and stored them under identical conditions to minimize variability. Essential equipment, including a camping stove, pot, ruler, and knife, was assembled for potato preparation.

To prepare the potatoes, we uniformly cut them into 4 by 5 cm cubes and weighed each batch to ensure consistency, with an average weight of around 90 grams, varying by only a few grams. Half of the potatoes were quartered, while the other half remained intact. Simultaneously, we boiled half of the batches in the same pot for 8 minutes, carefully monitoring the process to ensure uniformity. After boiling, the potatoes were laid out on paper towels to cool for 5 minutes, with the levels of each batch documented for reference.

During the experiment, one team member oversaw the reading of the run order and provided the correct batch of potatoes, while another inserted the electrodes to a consistent depth and wired them accordingly. The third member was responsible for connecting the meter and recording voltage in volts and amperage in milliamps. It was crucial to measure amperage within the first second to minimize interference from flesh oxidation around the electrodes.

Following the completion of the first replicate, the second replicate was immediately conducted with the same operators to maintain consistency. Finally, the room was cleaned to its original condition to ensure readiness for future use.

Despite our meticulous planning, we encountered no significant issues during the execution of the experiment. However, the potential influence of nuisance factors, such as variations in potato density or slight differences in electrode insertion depth, will be carefully considered during data analysis to ensure accurate interpretation of results.

Figure 1 Process of data collection

Data Analysis

The dataset was collected and recorded in the table below:

Potato	Boiled	State	Label	I1	V1	P1	I2	V2	P2
-	-	-	(1)	0.29	0.84	0.2436	0.34	0.84	0.2856
+	-	-	a	0.32	0.81	0.2592	0.41	0.84	0.3444
-	+	-	b	1.68	0.79	1.3272	1.67	0.80	1.3360
+	+	-	ab	2.15	0.83	1.7845	2.72	0.81	2.2023
-	-	+	c	0.70	0.84	0.5880	0.68	0.82	0.5576
+	-	+	ac	0.51	0.82	0.4182	0.82	0.85	0.6970
-	+	+	bc	2.88	0.79	2.2752	3.37	0.83	2.7971
+	+	+	abc	3.18	0.77	2.4486	3.67	0.83	3.0461

By looking at the table, we can see that the voltages are almost the same. However, the amperage which is the amount of electrical charge that is flowing through the circuit is significantly higher for high levels of each factor. This significant increase in the amperage then results in higher values of power. It seems that the results are promising and in line with what we expected based on the prior scientific findings. Although further investigation and data analysis gives us more definite results.

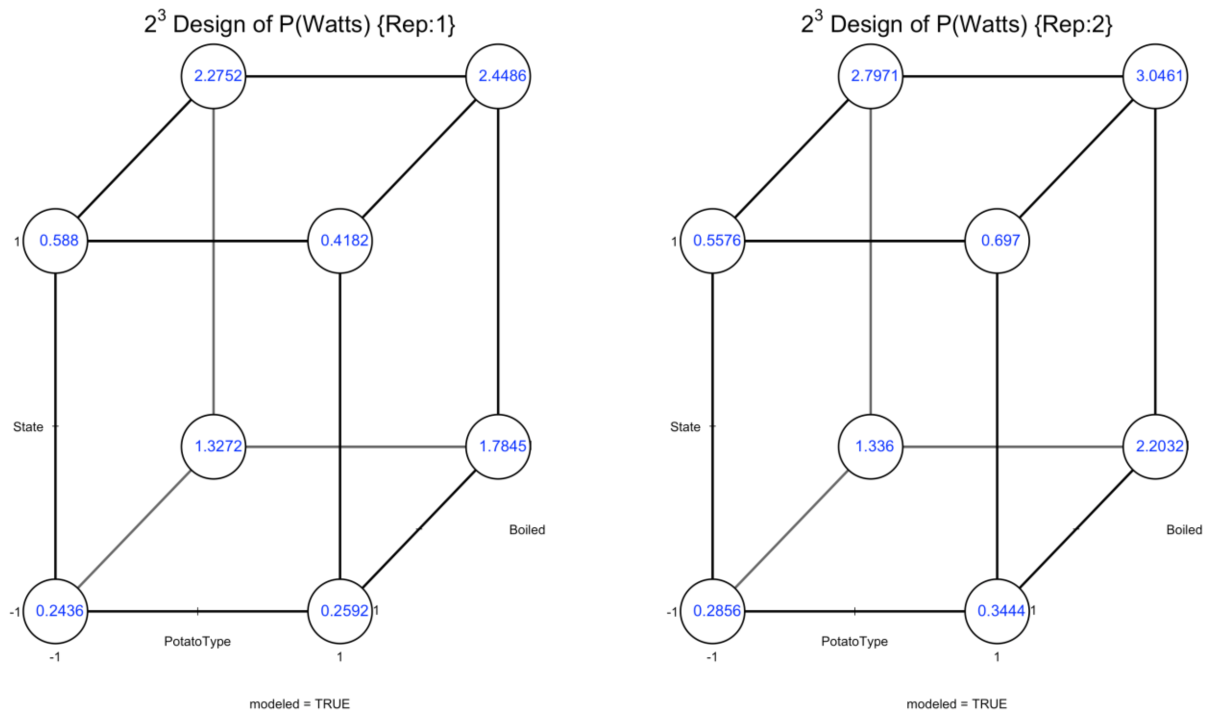


Figure 2 Cube plot of the data

By looking at the plots of cube representations of the datasets, we can see that the second replicate had higher WATTs which is a result of having more time to cool down. Moreover, we can see that boiling was more effective on the Russet potatoes since they are starchier than the yellow potatoes.

Following data collection, we proceeded to analyze the gathered information using R. Our initial step involved fitting the model with all the interaction terms to comprehensively assess the relationships between the various factors and the response variable. The output of this analysis is presented below for reference:

```
Call:
lm.default(formula = P ~ A * B * C + Block, data = Data)

Residuals:
   Min     1Q Median     3Q    Max
-0.179 -0.103  0.000  0.103  0.179

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   0.9277     0.1386    6.69  0.00028 ***
A             0.1119     0.0438    2.55  0.03792 *
B             0.8640     0.0438   19.71  2.2e-07 ***
C             0.3153     0.0438    7.19  0.00018 ***
Block         0.2403     0.0877    2.74  0.02888 *
A:B           0.1064     0.0438    2.43  0.04556 *
A:C          -0.0629     0.0438   -1.44  0.19426
B:C           0.1743     0.0438    3.98  0.00536 **
A:B:C        -0.0498     0.0438   -1.14  0.29306
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.175 on 7 degrees of freedom
Multiple R-squared:  0.986,     Adjusted R-squared:  0.969
F-statistic: 59.9 on 8 and 7 DF,  p-value: 9.28e-06
```

```
          Df Sum Sq Mean Sq F value  Pr(>F)
A          1   0.20    0.20    6.52 0.03792 *
B          1  11.94   11.94  388.48 2.2e-07 ***
C          1   1.59    1.59   51.72 0.00018 ***
Block      1   0.23    0.23    7.51 0.02888 *
A:B        1   0.18    0.18    5.89 0.04556 *
A:C        1   0.06    0.06    2.06 0.19426
B:C        1   0.49    0.49   15.80 0.00536 **
A:B:C      1   0.04    0.04    1.29 0.29306
Residuals  7   0.22    0.03
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 3 Coefficients and ANOVA table of the full model

After fitting the full model, it became evident from the output that the interaction terms A:B:C and A:C were not statistically significant and therefore should be removed from the model. The interaction term A:B:C indicates the combined effect of potato type, boiling condition, and potato state on the response variable (power output). However, since this interaction was not significant, it suggests that the relationship between these factors is not influential in determining the power output of the potato batteries. Similarly, the non-significant interaction term A:C implies that the relationship between potato type and potato state does not significantly impact power output. Therefore, we can simplify our model by removing these non-significant interactions, allowing for a more interpretable analysis of the factors influencing potato battery efficiency.

Following the identification of non-significant interaction terms, we proceeded to fit a reduced model incorporating only the remaining significant factors. The results of this analysis are presented below for reference.

```
Call:
lm.default(formula = P ~ A * B * C + Block - A:B:C - A:C, data = Data)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.29136 -0.07641  0.00457  0.08721  0.25356 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)    0.928      0.149    6.24  0.00015 ***
A              0.112      0.047    2.38  0.04118 *  
B              0.864      0.047   18.38  1.9e-08 ***
C              0.315      0.047    6.71  8.8e-05 ***
Block          0.240      0.094    2.56  0.03091 *  
A:B            0.106      0.047    2.26  0.04987 *  
B:C            0.174      0.047    3.71  0.00487 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.188 on 9 degrees of freedom
Multiple R-squared:  0.979,	Adjusted R-squared:  0.965 
F-statistic:   69 on 6 and 9 DF,  p-value: 5.17e-07
```

```
          Df Sum Sq Mean Sq F value  Pr(>F)    
A          1   0.20    0.20    5.67  0.0412 *  
B          1  11.94   11.94  337.71 1.9e-08 ***
C          1   1.59    1.59   44.96 8.8e-05 ***
Block      1   0.23    0.23    6.53  0.0309 *  
A:B        1   0.18    0.18    5.12  0.0499 *  
B:C        1   0.49    0.49   13.74  0.0049 ** 
Residuals  9   0.32    0.04                    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 4 Coefficient and ANOVA table of the reduced (final) model

Upon examining the final results output, it is evident that all the main effects are statistically significant. Additionally, the interaction between potato type and boiling condition emerges as significant, reinforcing our earlier conclusion that boiling has a more pronounced effect on Russet potatoes due to their higher starch content. This finding underscores the importance of considering the specific characteristics of potato varieties when optimizing battery efficiency. Furthermore, the significant interaction between boiling condition and potato state aligns with our initial observations and is supported by interaction plots. This suggests that the effectiveness of boiling may vary depending on whether the potato is used whole or quartered, highlighting the nuanced interplay between experimental factors in influencing potato battery performance.
The significant blocking effect we observed backs up our earlier idea that heat affects resistance. When we let the second batch of potatoes cool for longer, it decreased the resistance. This meant that more electric current could flow through, boosting the power output. So, by giving the potatoes more time to cool down, we were able to make the batteries work better. This shows how important it is to consider temperature when studying how potato batteries perform.

Finally, the final proposed model considering all the significant interactions is as follows:

$$Watts = \beta_0 + \beta_1 Potato + \beta_2 Boiled + \beta_3 State + \beta_4 Relicate + \beta_{12} Potato{:}\, Boiled + \beta_{23} Boiled{:}\, State$$

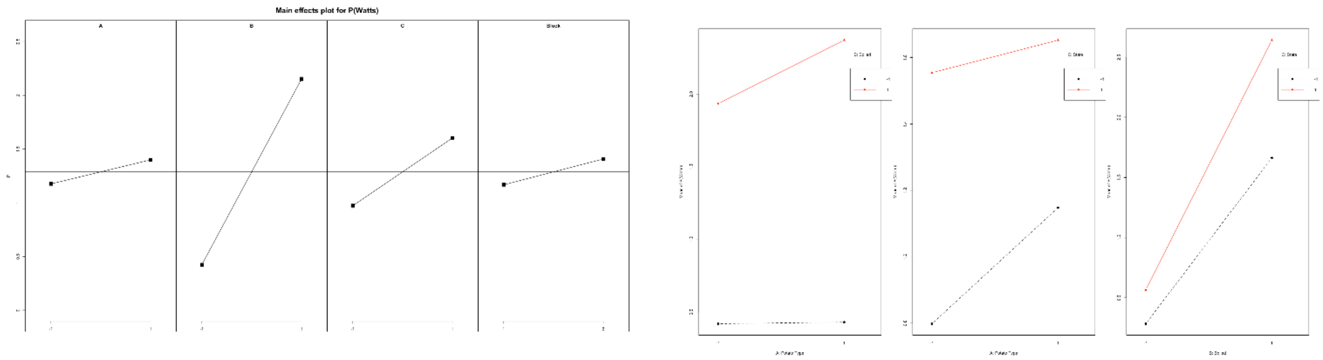


Figure 5 Main effects and Interaction plots

Upon reviewing the interaction plots, it becomes apparent that boiling emerges as the most significant main factor, exerting a substantial influence on potato battery performance. Conversely, the type of potato appears to be the least significant main factor in determining power output. This observation underscores the importance of boiling as a critical determinant of battery efficiency. It suggests that while potato type may contribute to variations in power output, the boiling process plays a more dominant role in enhancing overall battery performance.

After establishing the full model, we validated its accuracy by examining the residuals, which are the differences between the observed and predicted values. Our assessment revealed that the residuals exhibited a normal distribution, as indicated by a Shapiro-Wilk test p-value of approximately 1. Additionally, we observed no apparent pattern or trend in the residuals versus order plot, suggesting that they were independent of each other. Furthermore, the variance of the residuals appeared to be consistent across different levels of the predictor variables, as depicted in the residuals versus fitted values plot. Overall, these findings indicate that our model adequately captures the relationship between the predictor variables and the response variable, affirming its validity for further analysis and interpretation.

Appendix: Codes and Outputs

Codes:

```
rm(list = ls())
#install.packages("conf.design")
require("conf.design")
A=rep(rep(c(-1,1),4),each=2)
B=rep(rep(c(rep(-1,2),rep(1,2)),2),each=2)
C=rep(rep(c(rep(-1,4),rep(1,4)),1),each=2)
X=matrix(c(rep(1,16),A,B,C),nrow=16,ncol=4)
Block = rep(c(1,2),8)
I=c(0.29,0.34,0.32,0.41,1.68,1.67,2.15,2.72,0.7,0.68,0.51,0.82,2.88,3.37,3.18,3.67)
V=c(84,84,81,84,79,80,83,81,84,82,82,85,79,83,77,83)/100
P=I*V
Data <- data.frame(P, A,B,C, Block)
res.lm<-lm(P~A*B*C+Block, data=Data)
summary(res.lm)
res.aov<-aov(P~A*B*C+Block, data=Data)
summary(res.aov)

#install.packages("daewr")
library(daewr)
fullnormal(coef(res.lm)[-1],alpha=.5)

#Projected model
res.lm.p<-lm(P~A*B*C+Block-A:B:C, data=Data)
summary(res.lm.p)
res.aov.p<-aov(P~A*B*C+Block-A:B:C, data=Data)
summary(res.aov.p)

#Final model - remove non-significant terms
res.lm.f<-lm(P~A*B*C+Block-A:B:C-A:C, data=Data)
summary(res.lm.f)
res.aov.f<-aov(P~A*B*C+Block-A:B:C-A:C, data=Data)
summary(res.aov.f)

#Residual Analysis
#Normality
residuals.f=res.aov.f$residuals
qqnorm(residuals.f, ylim=c(min(residuals.f),max(residuals.f)), main = "Normal Q-Q Plot for
Residuals",
      xlab = "Theoretical Quantiles", ylab = "Sample Quantiles- Modified",
      plot.it = TRUE, datax = FALSE)

qqline(residuals.f, datax = FALSE, distribution = qnorm)

#Test normality using Shapiro Wilks
```

```
shapiro.test(residuals.f)

#Check Variance
Fitted_values=res.aov.f$fitted.values
plot(Fitted_values,residuals.f,ylab="Residuals",xlab="Fitted Values", main = "Checking for
Homogeneity of Variance")
abline(h=0, col = 2, lty = 2)

#Check Independence
plot(seq(1:length(residuals.f)),residuals.f,type="b",ylab="Residuals",xlab="Order", main =
"Checking for Independence of Residuals")
abline(h=0, col = 2, lty = 2)

#Check Residuals vs Factors
par(mfrow=c(1,3))
plot(A,residuals.f,ylab="Residuals",xlab="Factor A: Potato Type", main = "Residuals VS.
Factors", col = A+3)
abline(h=0, col = 2, lty = 2)

plot(B,residuals.f,ylab="Residuals",xlab="Factor B: Boiled", main = "Residuals VS. Factors",
col = B+3)
abline(h=0, col = 2, lty = 2)

plot(C,residuals.f,ylab="Residuals",xlab="Factor C: State", main = "Residuals VS. Factors", col
= C+3)
abline(h=0, col = 2, lty = 2)

par(mfrow=c(1,1))

library(DescTools)
PostHocTest(res.aov.f<-aov(P~factor(A)*factor(B)*factor(C)+Block-A:B:C-A:C, data=Data)
, method= "hsd")

#plots

#install.packages("FrF2")

library(FrF2)
Data1 <- Data[Data$Block==1,1:4]
colnames(Data1) <- c("Power","PotatoType", "Boiled", "State")
P.lm.1 <- lm(Power ~ PotatoType*Boiled*State , data = Data1)
cubePlot(P.lm.1, "PotatoType", "Boiled", "State", main = expression(paste(2^3, " Design of
P(Watts) {Rep:1}")), round=4)
Data2 <- Data[Data$Block==2,1:4]
colnames(Data2) <- c("Power","PotatoType", "Boiled", "State")
P.lm.2 <- lm(Power ~ PotatoType*Boiled*State , data = Data2)
```

```
cubePlot(P.lm.2, "PotatoType", "Boiled", "State", main = expression(paste(2^3, " Design of
P(Watts) {Rep:2}")), round=4)


#Main effect plots
MEPlot(res.lm.f, main = c("Main effects plot for P(Watts)"))
par(mfrow=c(1,3))
interaction.plot(x.factor     = Data$A,
                 trace.factor = Data$B,
                 response     = Data$P,
                 type="b",
                 col=c("black","red","green"),  ### Colors for levels of trace var.
                 pch=c(19, 17, 15),             ### Symbols for levels of trace var.
                 fixed=TRUE,                    ### Order by factor order in data
                 leg.bty = "o",
                 trace.label = "B: Boiled",
                 xlab = "A: Potato Type",
                 ylab = "Mean of P(Watts)",
                 )

interaction.plot(x.factor     = Data$A,
                 trace.factor = Data$C,
                 response     = Data$P,
                 type="b",
                 col=c("black","red","green"),  ### Colors for levels of trace var.
                 pch=c(19, 17, 15),             ### Symbols for levels of trace var.
                 fixed=TRUE,                    ### Order by factor order in data
                 leg.bty = "o",
                 trace.label = "C: State",
                 xlab= "A: Potato Type",
                 ylab = "Mean of P(Watts)")

interaction.plot(x.factor     = Data$B,
                 trace.factor = Data$C,
                 response     = Data$P,
                 type="b",
                 col=c("black","red","green"),  ### Colors for levels of trace var.
                 pch=c(19, 17, 15),             ### Symbols for levels of trace var.
                 fixed=TRUE,                    ### Order by factor order in data
                 leg.bty = "o",
                 trace.label = "C: State",
                 xlab= "B: Boiled",
                 ylab = "Mean of P(Watts)")
par(mfrow=c(1,1))
#install.packages("pid")
library(pid)
```

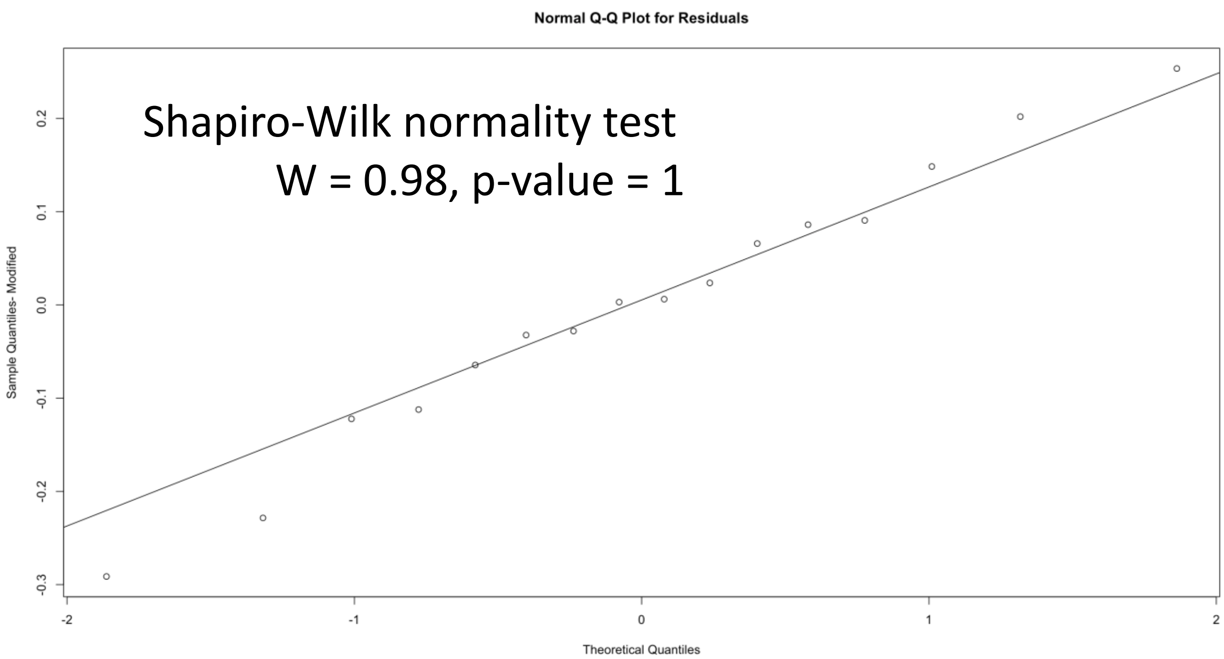
```
contourPlot(res.lm.f,
        main="Contour plot", "A","B",
        colour.function=terrain.colors)
contourPlot(res.lm.f,
        main="Contour plot", "A","C",
        colour.function=terrain.colors)
contourPlot(res.lm.f,
        main="Contour plot", "B","C",
        colour.function=terrain.colors)
```

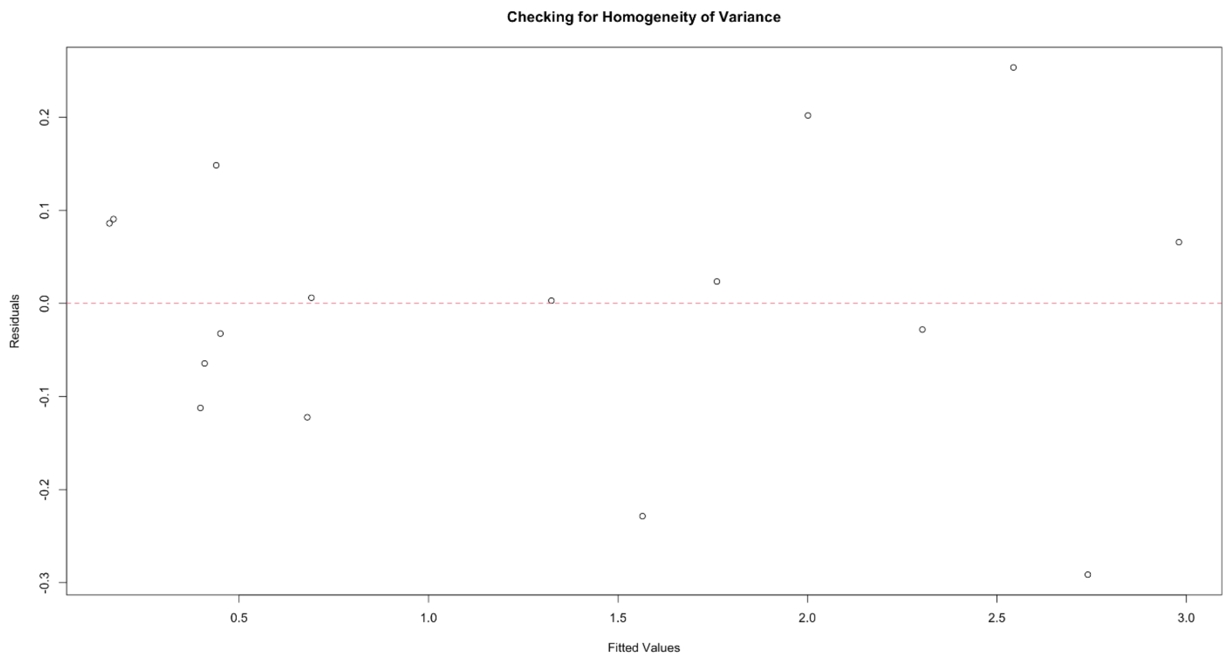
Outputs:

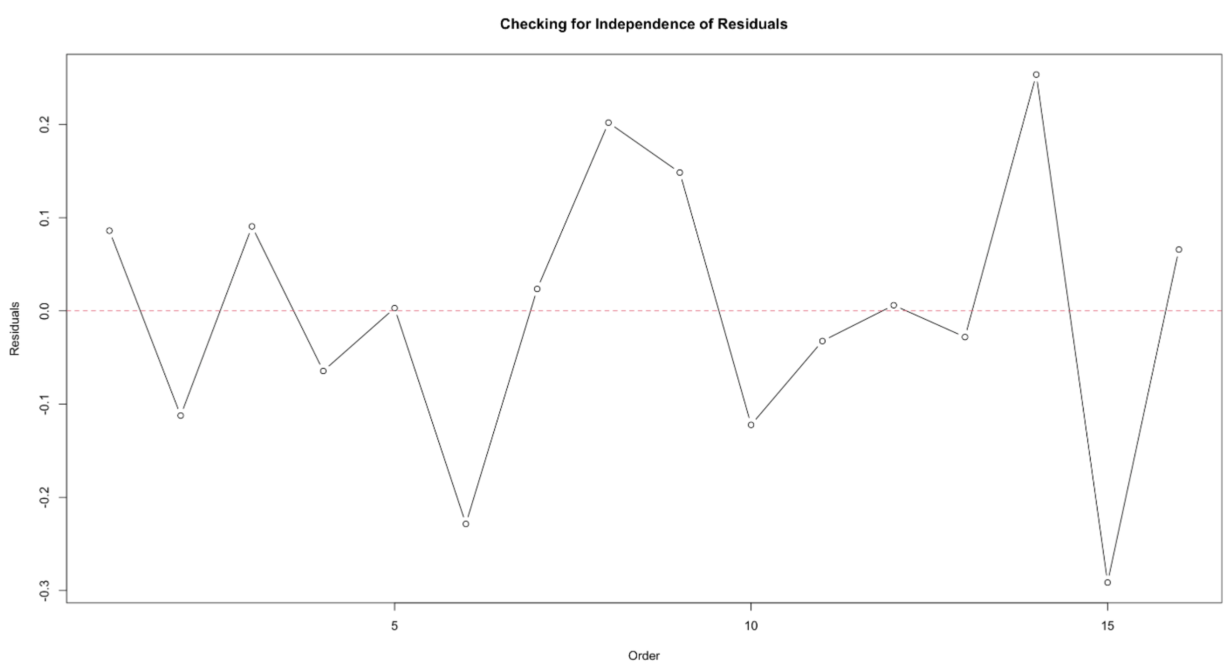
Run Order Randomization

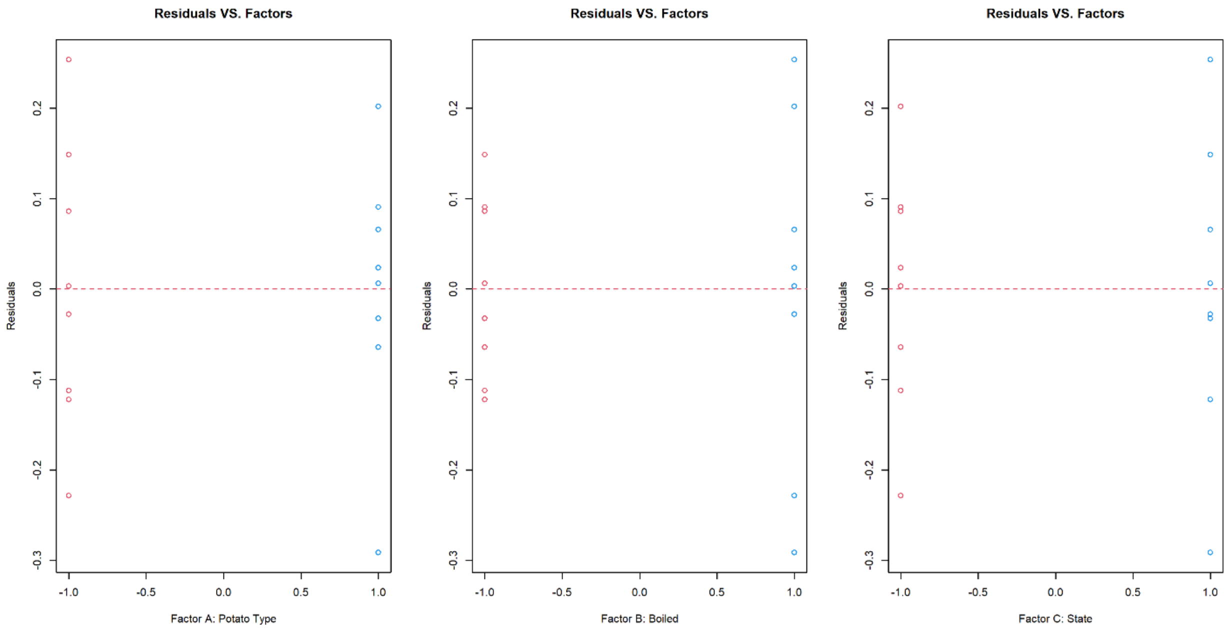
```
> set.seed(54)
> sample(1:8,8)
[1] 8 7 6 2 3 1 5 4
> set.seed(75)
> sample(1:8,8)
```

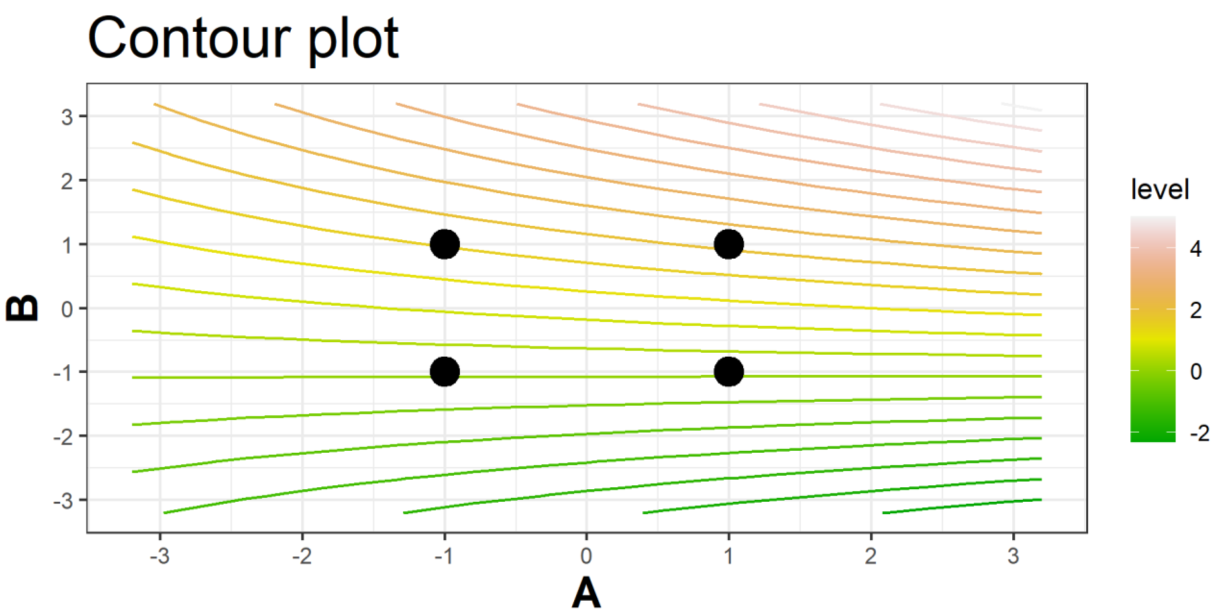
Residual Analysis

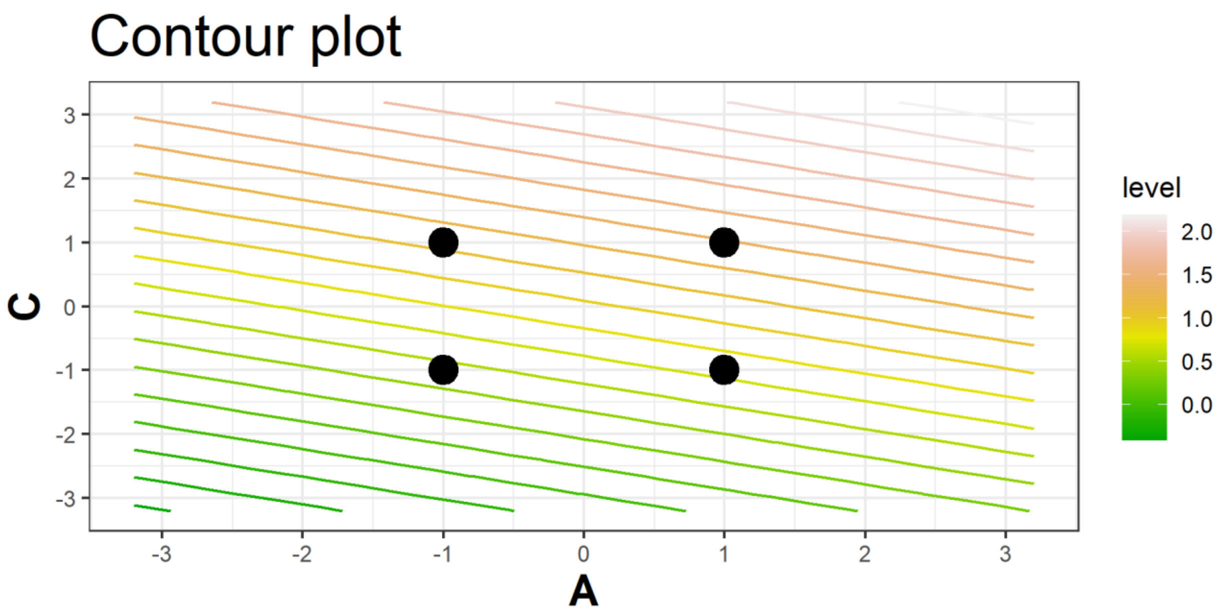



Checking for Homogeneity of Variance
Residuals
Fitted Values
0.5
1.0
1.5
2.0
2.5
3.0
-0.3
-0.2
-0.1
0.0
0.1
0.2

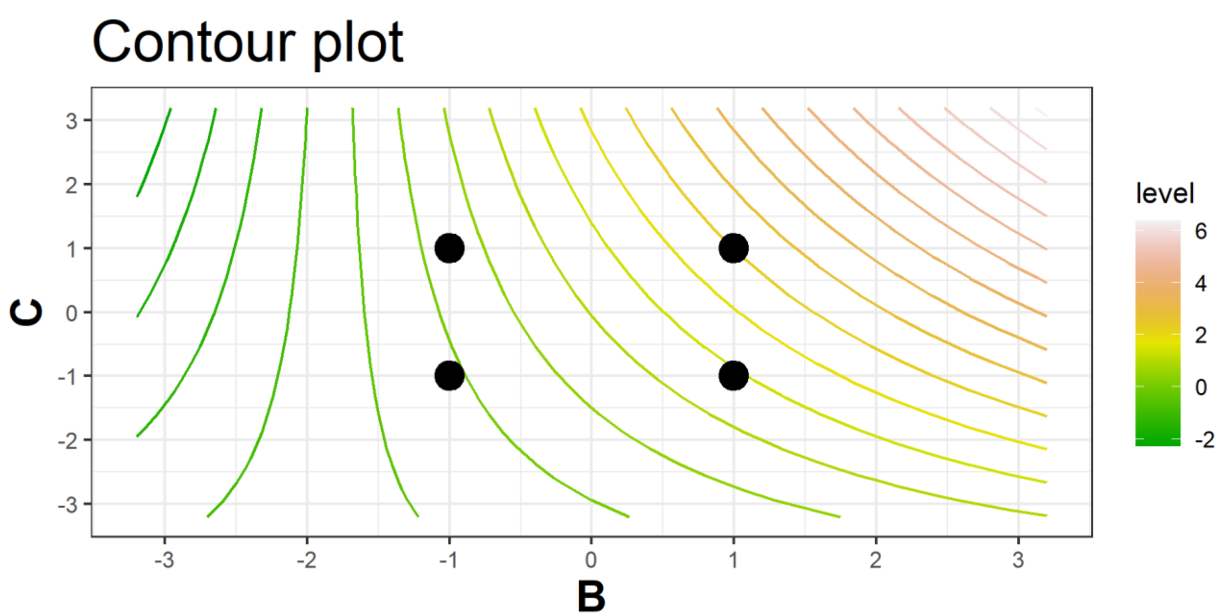

Checking for Independence of Residuals
Residuals
Order
5
10
15
-0.3
-0.2
-0.1
0.0
0.1
0.2


Residuals VS. Factors
Residuals
Factor A: Potato Type
Residuals VS. Factors
Residuals
Factor B: Boiled
Residuals VS. Factors
Residuals
Factor C: State
0.2
0.1
0.0
-0.1
-0.2
-0.3
-1.0
-0.5
0.0
0.5
1.0


Contour plot
B
A
level
4
2
0
-2



Contour plot
C
A
level
2.0
1.5
1.0
0.5
0.0



Contour plot
C
B
level
6
4
2
0
-2

References

Golberg, Alexander, Haim Rabinowitch, and Boris Rubinsky. 2010. “Zn/Cu-Vegetative Batteries, Bioelectrical Characterizations, and Primary Cost Analyses.” *Journal of Renewable and Sustainable Energy* 2 (May). https://doi.org/10.1063/1.3427222.