BE2100 Project Report – Variance in Resistors Resistances

Introduction

Electronics are a daily aspect of all of our modern routines and quality of life. From our phones, watches, and computers, all the way up to our power grids and cities. These complex systems all require the usage of resistors in order to function properly to serve our daily needs and wants. The quality of a resistor is essential to any product that is created to serve these interests, as everyday consumers and global companies all require them to thrive. When analyzing the quality of a resistor we look at its resistance, measured in Ohms(Ω), to help us understand how much it is affecting the current of a circuit, measured in Amps(A). We decided to look at different resistance measurements from two manufacturers and analyze the variance in resistance for various resistors produced by these manufacturers.

Outline of the Approach

1. Data collection

To gather data in this experiment, we needed to get the resistance measurements of many resistors from both manufacturers. In order to cut down on unwanted variables, we made sure to do 3 different values of resistors, as well as conducted the same trial many times for each value of resistor. (10 ohms, 2 Kilo ohms and 1 Mega ohm). This is important because increasing the sample size would allow us to see any differences or show us the lack of difference.

2. Statistics and Visualization

In order to understand the distribution of the data, we need something to show the comparison between values. To help us with visualizing our data, we used histograms, box plots as well as Tableau gauges. The histograms allowed us to see the mean and median of the data (center section). The box plots helped us see if there were outliers in our data distribution as well as compare the variance in between brands. We also used Tableau gauges to see the data spread visually (all at once).

3. Statistics Analysis

We calculated the mean resistance, standard deviation and the percentage error of the resistor groups to see the deviations between the other groups of resistor values in order to determine if the differences were significant. To determine if the difference was significant we used the t-tests and made confidence intervals, these analysis tests helped us see if they were significantly different.

Collected Data

1. 10Ω Resistor Data for BOJACK and Essmetuin

1	**BOJACK 10Ω**	**ESSMETUIN 10Ω**
2	10.15	10.06
3	10.12	10.13
4	10.2	10.18
5	10.12	10.12
6	10.06	10.11
7	10.03	10.15
8	10.05	10.17
9	10.04	10.14
10	10.11	10.18
11	10.07	10.15
12	10.06	10.09
13	10.16	10.1
14	10.1	10.03
15	10.11	10.1
16	10.22	10.07
17	10.06	10.02
18	10.14	10.04
19	10.06	9.98
20	10.07	10.05
21	10.11	10.01
22	10.17	10.12
23	10.03	10.26
24	10.13	10.34
25	10.14	10.23
26	10.07	10.2
27	10.09	10.22
28	10.1	10.13
29	10.19	10.38
30	10.15	10.17
31	10.18	10.09

2. 2kΩ Resistor Data for BOJACK and Essmetuin

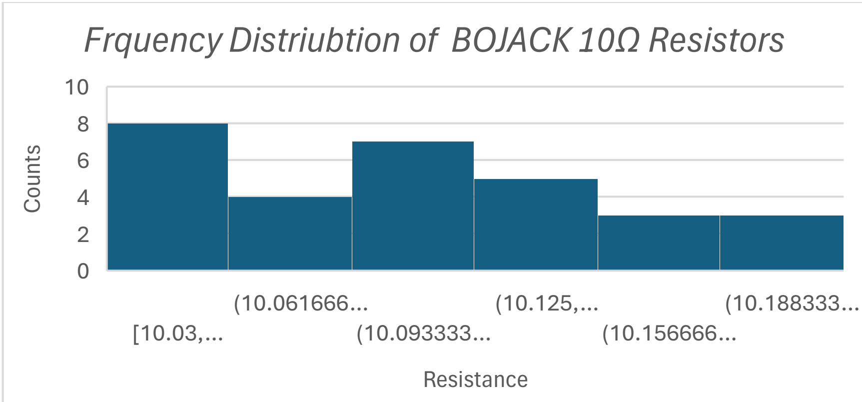
BOJACK 2kΩ	ESSMETUIN 2kΩ
1.9633	1.9518
1.9478	1.9533
1.952	1.965
1.972	1.977
1.9605	1.9534
1.9564	1.956
1.9683	1.9525
1.9622	1.9647
1.9497	1.9522
1.9646	1.9619
1.9723	1.9683
1.9744	1.9563
1.9508	1.9632
1.9477	1.9548
1.9729	1.967
1.9809	1.948
1.9443	1.9622
1.9544	1.9696
1.9686	1.9733
1.9545	1.927
1.9494	1.9226
1.9565	1.9264
1.9618	1.9515
1.965	1.9592
1.9568	1.9372
1.9549	1.9215
1.9685	1.9546
1.9671	1.9223
1.9546	1.9682
1.9713	1.9593

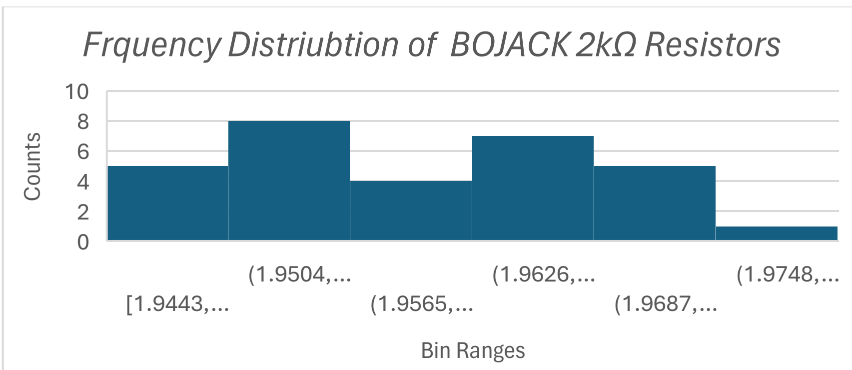
3. 1MΩ Resistor Data for BOJACK and Essmetuin

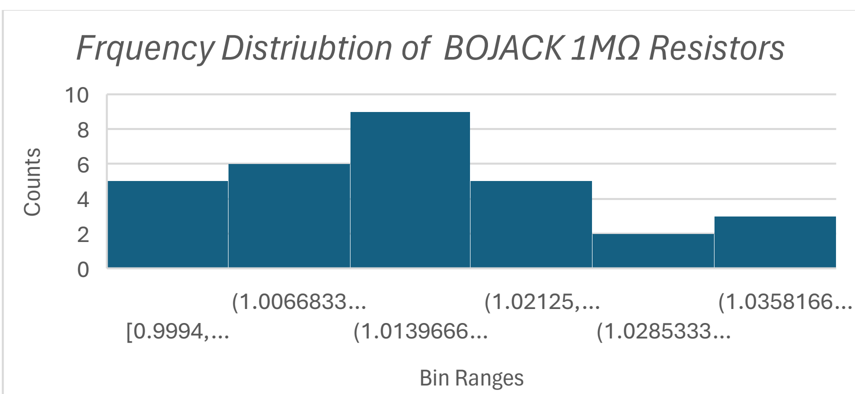
BOJACK 1MΩ	ESSMETUIN 1MΩ
1.0142	1.0303
1.0198	0.9673
1.001	0.9943
1.0074	0.9747
1.0308	0.9993
1.0205	0.9678
1.016	0.9711
1.0368	0.9823
1.0278	0.9796
1.0117	0.9906
1.0263	1.0287
1.0027	1.0244
1.0142	1.0021
1.0257	0.9998
1.0106	1.0318
1.0431	1.02
1.0383	1.0071
1.0252	1.0152
1.0176	1.0033
1.0142	0.978
1.0119	0.988
1.0138	0.9915
1.017	0.9897
1.0036	0.9922
1.0052	0.9801
1.0352	0.9889
1.0249	0.9853
0.9994	0.9829
1.0091	0.9994
1.0202	0.9787

Histograms

- BOJACK Histograms of 10Ω, 2kΩ, and 1MΩ Resistor Data

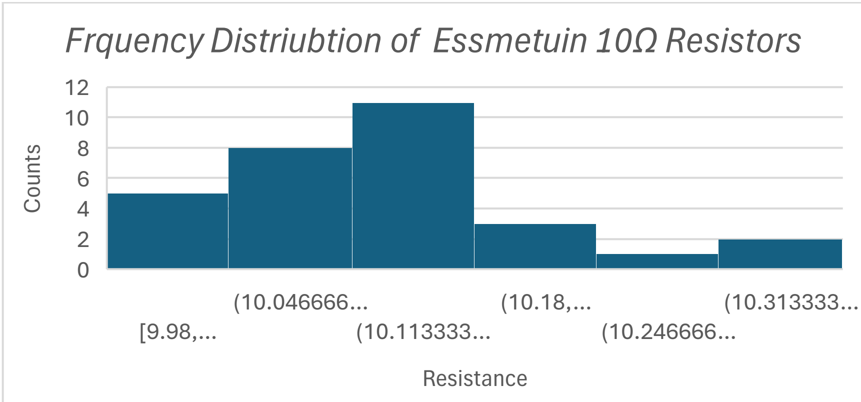


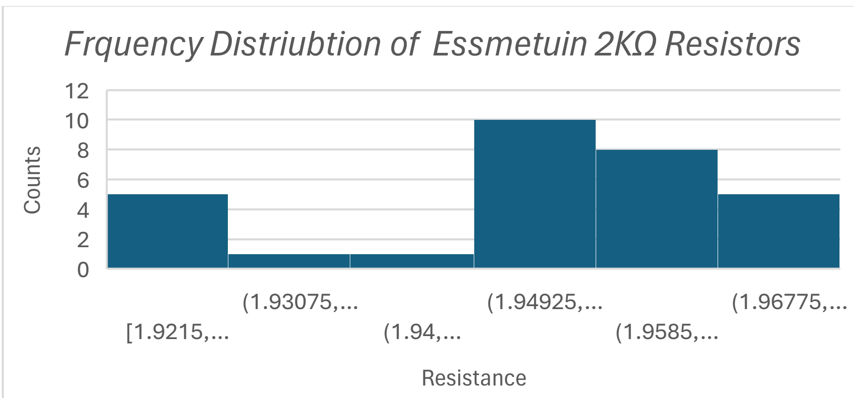


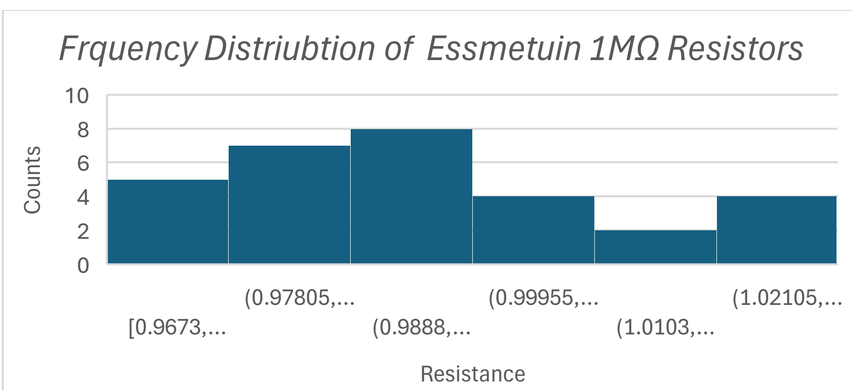


- The histograms suggest that through differing resistance values, the central tendency of the resistances have an error magnitude of about 1% – 2.5%. This is far within reach of the claims that BOJACK is making about their resistor tolerance rating.
- When observed all together, the histograms suggest that there isn't a singular direction skew or shift in the observed resistor values with respect to target. This implies that the deviation from target is likely random
- The histogram for the 2kΩ resistors might be bimodal, more information is needed

- Essmetuin Histograms of 10Ω, 2kΩ, and 1MΩ Resistor Data



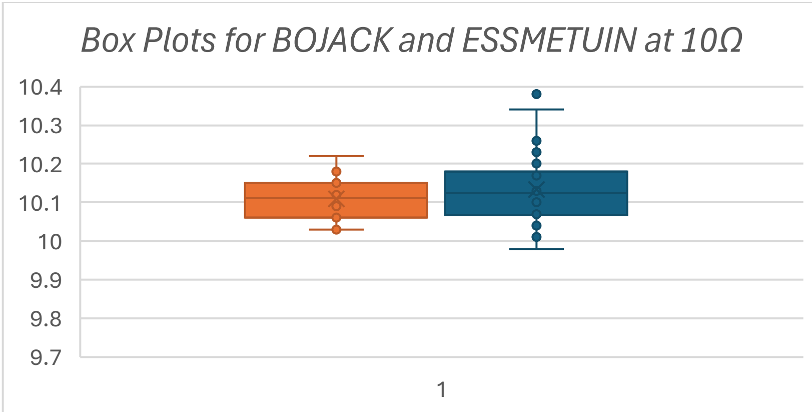


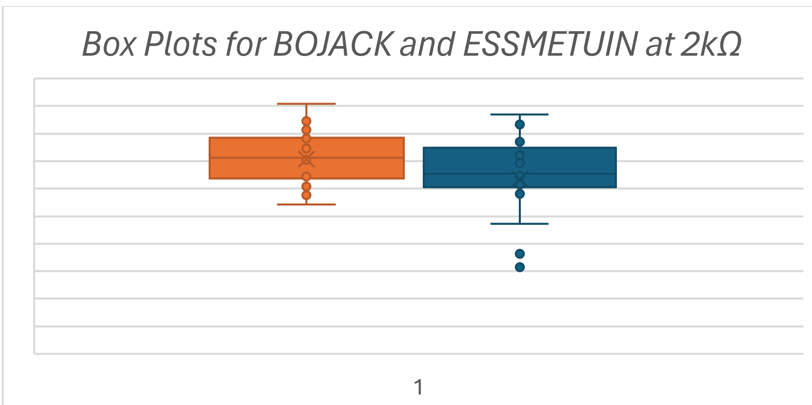


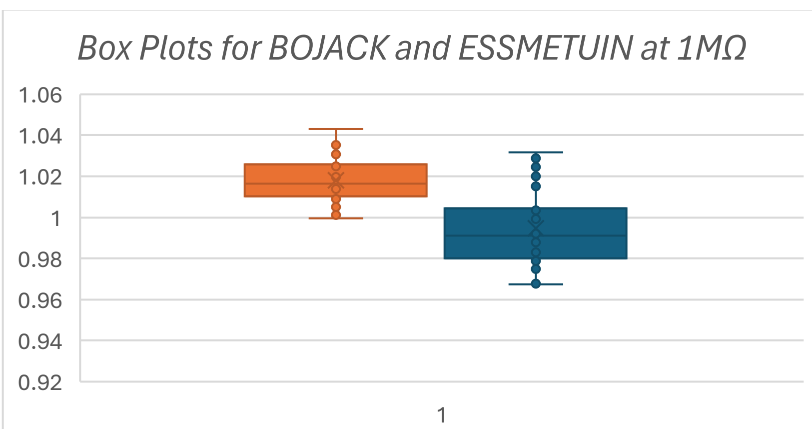
- Much like BOJACK, the central tendencies of the data for Essmetuin lie between 1% - 2.5%. Based on this data both resistor distributors have acceptable values with respect to their tolerance claims
- Something important to note is there is a significant number of resistors that lie near ±5% tolerance boundary. That could mean there are two central tendencies, where one is a tendency to be defective.
- Though the 1MΩ resistor tend to have a 1% tolerance, however the data spans from -3% to 3% tolerance.

Box Plots

- Box Plots comparing resistors values at 10Ω, 2kΩ, and 1MΩ



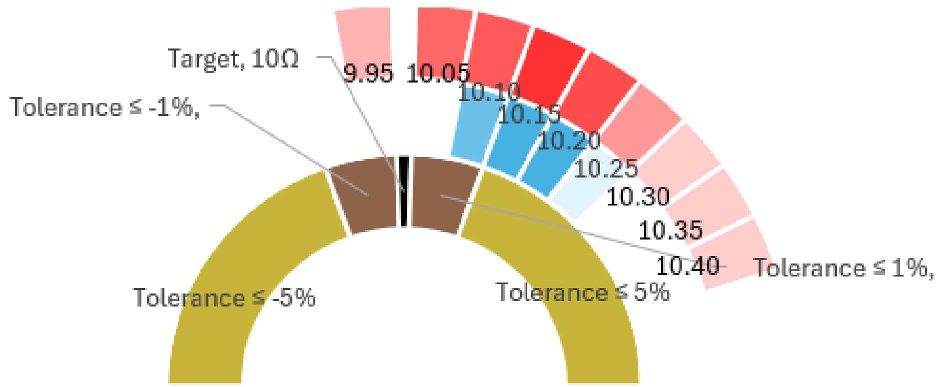


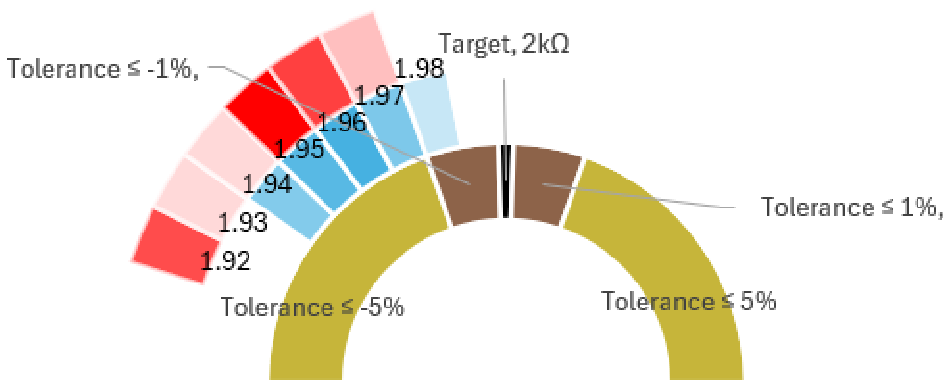


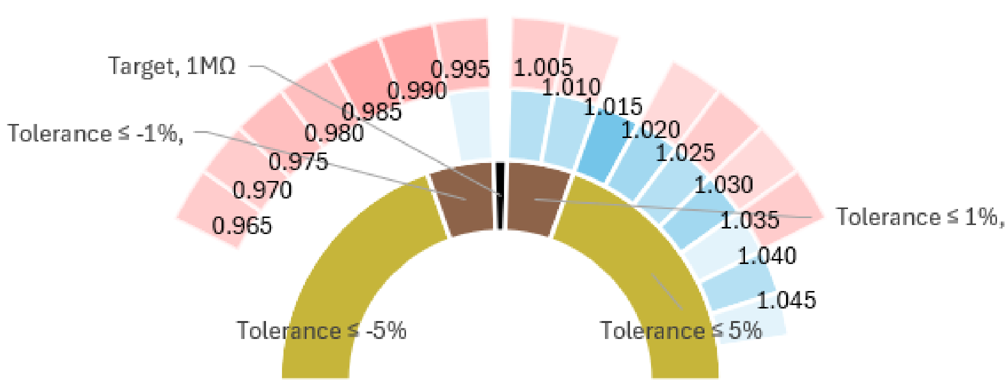
- BOJACK has a significantly tighter spread regarding the variance of its data points.
- BOJACK tends to trend more towards target. In the data for 1MΩ Essmetuin tends closer to target, however it has a lot of spread and variance comparatively.
- Essmetuin seems to have a decent number of outliers. A couple of these outliers coincide with that group of resistors close to the acceptable tolerance boundary. This could pose an issue, but more evaluation is required.

Tableau Gauges (Data Visualization)

- These gauges were constructed with the intent of better visualizing trends in the data
- Tableau gauges for the 10Ω, 2kΩ, and 1MΩ data







Summary of Descriptive Statistics

These descriptive statistics that we gathered from our resistor samples let us visualize the reliability and quality of each of our manufactures. For each nominal resistance value, we calculated the mean, standard deviation, and created visuals. Using our key graphs, we can see that BoJack branded resistors were more consistent with the written specifications. We can see this by taking a look and comparing our confidence intervales and standard deviations.

In our statical Interval section we delve deeper into the actual values we obtained using confidence intervales and standard deviations formulas.

	BOJACK 10Ω	ESSMETUIN 10Ω	BOJACK 2kΩ	ESSMETUIN 2kΩ	BOJACK 1MΩ	ESSMETUIN 1MΩ
Mean	10.1097	10.1340	1.9608	1.9533	1.0181	0.9948
Median	10.1100	10.1250	1.9612	1.9554	1.0165	0.9911
Mode(s)	10.06	10.13	0.00	0.00	1.01	0.00
Variance	0.00275505747126	0.00836965517241	0.00009006833333	0.00024468185057	0.00013180110345	0.00034549291954
Standard Deviation	0.052488641	0.09148582	0.009490434	0.01564231	0.011480466	0.01858744
Sample Size	180					

Statistical Intervals

A. Justification / Discussion of how and why this is being used.

Statistical intervals, specifically confidence intervals, help estimate where the true rate means resistance of a resistor brand likely falls. Instead of relying solely on the sample mean, a CI shows a range where we are statistically confident the true value lies. This is useful for comparing brands like Bojack and Essmetuin. Checking quality against industry standards and tolerance limits. Understanding precision how smaller CI range gives more consistent resistors. Confidence intervals provide a quantitative way to evaluate and defend our findings.

B. Assumptions.

To correctly use statistical intervals, we assume normality, random sampling, independence, and estimated standard deviation. For normality in this care the resistance data is approximately normally distributed reasonable due to physical measurement and decent sample sizes. The resistors were randomly sampled for random sampling. Each measurement is independent. Since population deviation is unknown, we use the t-distribution to estimate.

C. Analysis.

Confidence Interval 95% for the Mean:

Sample size (n): 30

Degree of freedom (df): 29

t = 2.045

10-ohm resistors:

Bojack:

Mean: 10.115

Standard deviation: 0.051

CI = $10.115 \pm 2.045 \times \frac{0.051}{\sqrt[2]{30}} = [10.096,\ 10.134]$

Essmetuin:

Mean: 10.133

Standard deviation: 0.088

CI = $10.133 \pm 2.045 \times \frac{0.088}{\sqrt[2]{30}} = [10.100,\ 10.166]$

2k ohm resistors:

Bojack:

Mean: 1.961

Standard deviation: 0.010

CI = $1.961 \pm 2.045 \times \frac{0.010}{\sqrt[2]{30}} = [1.956,\ 1.965]$

Essmetuin:

Mean: 1.953

Standard deviation: 0.016

CI = $1.953 \pm 2.045 \times \frac{0.016}{\sqrt[2]{30}} = [1.947,\ 1.959]$

1M ohm resistors:

Bojack:

Mean: 1.017

Standard deviation: 0.012

CI = $1.017 \pm 2.045 \times \frac{0.012}{\sqrt[2]{30}} = [1.013,\ 1.021]$

Essmetuin:

Mean: 0.995

Standard deviation: 0.019

CI = $0.995 \pm 2.045 \times \frac{0.019}{\sqrt[2]{30}} = [0.988,\ 1.002]$

Hypothesis Test

A. Justification

Hypothesis testing gives us the ability to determine the probability that the population from which our samples were gathered is centered at the labeled value of the resistor. Due to the nature of resistors and their tolerance ratings, hypothesis testing might result in some not-so-clear results. This will likely result in the population mean not falling on the labeled value, but all the resistors still falling within the tolerance. To verify that the population mean does not fall outside of the bounds of ±5%, two one-sided hypothesis tests can be conducted to determine the probability of the population mean falling within those bounds.

B. Assumptions

Our initial assumptions are that the sample data is normal and random, with each sample being independent. These tests will not be assuming that the sample variance represents the population variance, and t-tests will be conducted to determine the probability. The alpha value that we will be using is 0.05. For the hypothesis testing, we will be assuming that the population mean is equal to the labeled value of the resistors, which will be our null hypothesis. Our first alternate hypothesis will be that the population mean does not equal that value:

$$H_0: \mu_0 = Labeled\ W$$

$$H_a: \mu_a \neq Labeled\ W$$

Since there can be a ±5% variation on the resistor measurement, it isn't necessary for the population mean to fall exactly at the labeled value. However, it is important that the population mean falls between ±5% of the labeled resistance, and we will test this range if the population mean seems unlikely to be exactly the labeled resistance.

$$H_0: \mu_0 = Labeled\ W\ + 5\%$$

$$H_a: \mu_a < Labeled\ W\ + 5\%$$

This hypothesis will be tested, as well as the following hypothesis:

$$H_0: \mu_0 = Labeled\ W\ - 5\%$$

$$H_a: \mu_a > Labeled\ W\ - 5\%$$

C. Analysis

From the data that was collected we can derive this chart of sample means and standard errors

	Sample Mean ($\bar{x}$)	Standard Error (SE)
BOJACK 10Ω	10.10966667	0.009583071
BOJACK 2kΩ	1.960783333	0.001732708
BOJACK 1MΩ	1.018140	0.002096036
ESSMETUIN 10Ω	10.134	0.016702949
ESSMETUIN 2kΩ	1.953343333	0.002855881
ESSMETUIN 1MΩ	0.9948133333	0.003393586

It should be noted that within this chart, the standard error is very lower for each resistor value. The t-test value will be determined with the following equation:

$$t_o = \frac{\bar{x} - \mu_o}{SE}$$

Finding the probability from these values, using 29 degrees of freedom, produces these results:

	t_o	p
BOJACK 10Ω	11.44379157	2.84428E-12
BOJACK 2kΩ	-22.63316247	5.60467E-20

BOJACK 1MΩ	8.654428354	1.57285E-09
ESSMETUIN 10Ω	8.022535415	7.56874E-09
ESSMETUIN 2kΩ	-16.33704318	3.63979E-16
ESSMETUIN 1MΩ	-1.528373115	0.137255095

With an alpha of 0.05, the only null hypothesis we fail to reject is the Essmetuin 1MΩ, suggesting that this is the only sample that is more than 5% likely to come from a population that has a mean centered around the labeled value of the resistor. The other values are as small as they are because the standard error is so low.

This isn't to say that the resistors are lying, and to prove that the population that resistors come from is true to the label with its tolerance, we can test the null hypothesis that the population mean is at the upper and lower limits, with the alternate hypothesis being that the population mean is within the parameters. Testing the upper limit is done with:

$$t_o = \frac{\bar{x} - Labeled\ W\ \ + 5\%}{SE}$$

And testing the lower limit is done with:

$$t_o = \frac{\bar{x} - Labeled\ W\ \ - 5\%}{SE}$$

Which gives us these results

	$\mu_0 = Labeled\ W\ \ + 5\%$	$\mu_0 = Labeled\ W\ \ - 5\%$
BOJACK 10Ω	0	0
BOJACK 2kΩ	0	0
BOJACK 1MΩ	0	0
ESSMETUIN 10Ω	0	0
ESSMETUIN 2kΩ	0	0
ESSMETUIN 1MΩ	0	0

In each case here we can see that the null hypothesis is rejected, and the population mean is greater than the labeled value minus five percent, but lower than the labeled value plus five percent.

Regression Analysis

A. Justification

We used simple linear regression to examine whether the average percent error in resistance increases with nominal resistance across two brands, BOJACK and ESSMETUIN. This method was chosen because it allows us to model the relationship between a continuous predictor (resistance) and a continuous outcome (percent error). Since we only had three resistance levels 10 Ω, 2 KΩ, and 1 MΩ—regression provided a clear way to detect any trends. All data processing, calculations, and graphing were done using MATLAB, including the computation of average percent errors, generation of t-test and ANOVA results, and plotting of fit lines. We used a logarithmic scale on the x-axis of our graph because the resistance values span several orders of magnitude, and a log scale makes the differences between small and large values easier to visualize and compare. A linear fit line was included to help visualize the overall trend and determine whether the relationship between resistance and percent error followed a consistent linear pattern.

B. Assumption

For this regression model, we assumed that there is a straight-line relationship between resistance and percent error. We also assumed that the error in our measurements is random, not biased in any direction, and that the differences between the actual data and the model's predictions are spread out in a fairly consistent way. Since we calculated average percentage errors from 30 samples for each resistor type, this helps reduce the effect of any unusual or extreme values. While we only tested three resistance levels, we treated resistance as a continuous variable so we could fit and test a regression line.

C. Analysis

The regression results did not support a statistically significant linear relationship between resistance and percent error for either brand. Both the t-tests for the slope coefficients and the ANOVA tables yielded p-values well above 0.05, indicating that we failed to reject the null hypothesis. The slope values were small and close to zero, suggesting a weak or negligible trend. Additionally, the F-statistics were low, reinforcing the conclusion that the models explain very little of the variation in the data. Overall, we observed no strong evidence that average percent error increases with resistance in a linear fashion within the tested range

New to MATLAB? See resources for Getting Started.

```
>> BE2100_FP1
BOJACK Coefficients (T-Test)
```

	Estimate	SE	tStat	pValue
(Intercept)	1.528	0.43223	3.5352	0.17549
x1	2.9083e-07	7.4864e-07	0.38848	0.76411

Table 1: BOJACK T-test Coefficients (above)

BOJACK ANOVA TABLE

ans =

2x5 table

	SumSq	DF	MeanSq	F	pValue
x1	0.056276	1	0.056276	0.15092	0.76411
Error	0.37289	1	0.37289		

Table 2: BOJACK ANOVA Table (above)

New to MATLAB? See resources for Getting Started.

--- ESSMETUIN Coefficients (T-Test) ---

	Estimate	SE	tStat	pValue
(Intercept)	1.8428	0.49048	3.7572	0.1656
x1	-2.3719e-07	8.4953e-07	-0.2792	0.82667

Table 3: ESSMETUIN T-test Coefficients (above)

--- ESSMETUIN ANOVA Table ---

ans =

2x5 table

	SumSq	DF	MeanSq	F	pValue
x1	0.037431	1	0.037431	0.077953	0.82667
Error	0.48017	1	0.48017		

Table 4: ESSMETUIN ANOVA Table (above)

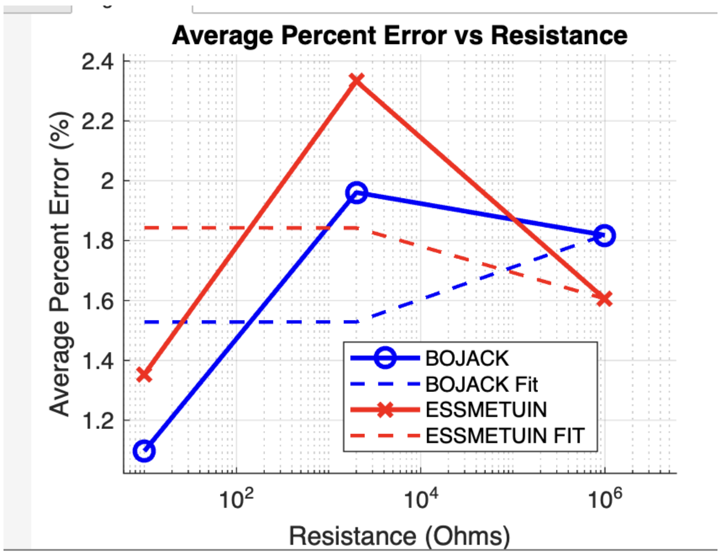


Figure 1: Regression Plot – Average Percent Error vs Resistance (Log Scale) (above)

Note: Resistance is shown on a logarithmic scale to clearly display values that span multiple orders of magnitude (10 Ω to 1 MΩ). This helps avoid crowding of lower values and allows for better comparison across all resistance levels.

Discussion and Conclusion

A. Summary of Performance/ Findings

Overall, the data that we have collected on both BoJack and Essmetuin resistors reveals that they fell into their expected nominal values. Shown by our statistical intervals, we can conclude that BoJack resistors were more reliable and consistent in all our experimental tests. This is not to say that Essmetuin is unusable—rather our findings show that Essmetuin displayed more variation and deviation from the specific values labeled ob tge resistance.

B. Interpretation of the Graphs

These graphs help us gather insight into the data that we have collected. Specifically, our box plot has shown that the ranges of our taken data of BoJack are significantly tighter and there are fewer outliers in our data, in comparison to the Essmetuin data. This corresponds to our statistical intervals, which gives us evidence that our findings are correct.

C. What to investigate next

Why does Essmetuin seem to have higher variability?

How do these slight variations affect circuits?

Will a larger sample size show prove our assumptions were correct about the two manufacturers?

Bojack resistors showed consistency and reliability making them a superior choice for those who are looking for precise resistors for electronics. Essmetuins variability can be seen as a downside to these resistors. Digging for the root causes of such variability can be beneficial to making informed and correct purchasing decisions.

Appendixes

MATLAB CODE FOR REGRESSION (SEE NEXT PAGE)

BE2100_FP1.m × BE2100_FP3.m × +

/MATLAB Drive/BE2100_FP1.m

```matlab
nominals = [10, 2000, 1e6];
boj_10 = [10.15,10.12,10.2,10.12,10.06,10.03,10.05,10.04,10.11,10.07,...
          10.06,10.16,10.1,10.11,10.22,10.06,10.14,10.06,10.07,10.11,...
          10.17,10.03,10.13,10.14,10.07,10.09,10.1,10.19,10.15,10.18];
boj_2k = [1.9633,1.9478,1.952,1.972,1.9605,1.9564,1.9683,1.9622,1.9497,1.9646,...
          1.9723,1.9744,1.9508,1.9477,1.9729,1.9809,1.9443,1.9544,1.9686,1.9545,...
          1.9494,1.9565,1.9618,1.965,1.9568,1.9549,1.9685,1.9671,1.9546,1.9713];
boj_1M = [1.0142,1.0198,1.001,1.0074,1.0308,1.0205,1.016,1.0368,1.0278,1.0117,...
          1.0263,1.0027,1.0142,1.0257,1.0106,1.0431,1.0383,1.0252,1.0176,1.0142,...
          1.0119,1.0138,1.017,1.0036,1.0052,1.0352,1.0249,0.9994,1.0091,1.0202];
ess_10 = [10.06,10.13,10.18,10.12,10.11,10.15,10.17,10.14,10.18,10.15,...
          10.09,10.1,10.03,10.1,10.07,10.02,10.04,9.98,10.05,10.01,...
          10.12,10.26,10.34,10.23,10.2,10.22,10.13,10.38,10.17,10.09];
ess_2k = [1.9518,1.9533,1.965,1.977,1.9534,1.956,1.9525,1.9647,1.9522,1.9619,...
          1.9683,1.9563,1.9632,1.9548,1.967,1.948,1.9622,1.9696,1.9733,1.927,...
          1.9226,1.9264,1.9515,1.9592,1.9372,1.9215,1.9546,1.9223,1.9682,1.9593];
ess_1M = [1.0303,0.9673,0.9943,0.9747,0.9993,0.9678,0.9711,0.9823,0.9796,0.9906,...
          1.0287,1.0244,1.0021,0.9998,1.0318,1.02,1.0071,1.0152,1.0033,0.978,...
          0.988,0.9915,0.9897,0.9922,0.9801,0.9889,0.9853,0.9829,0.9994,0.9787];

% So made a annoynomus function to use later for calculations
get_errorv = @(measured, nominal) abs((measured - nominal) ./ nominal) * 100;

%average percent errors celculatioon for boj
boj_error = [mean(get_errorv(boj_10, nominals(1))), ...
             mean(get_errorv(boj_2k * 1000, nominals(2))), ...
             mean(get_errorv(boj_1M * 1e6, nominals(3)))];

%average percent errors celculatioon for ess
ess_error = [mean(get_errorv(ess_10, nominals(1))), ...
mean(get_errorv(ess_2k * 1000, nominals(2))), ...
mean(get_errorv(ess_1M * 1e6, nominals(3)))];


% linear regression for BOJACK
mdl_boj = fitlm(nominals, boj_error);
% T-test coefficients
disp('BOJACK Coefficients (T-Test)');
disp(mdl_boj.Coefficients);
%  ANOVA table
disp('BOJACK ANOVA TABLE');
anova(mdl_boj)


% linear regression for ESSMETUIN
mdl_ess = fitlm(nominals, ess_error);
% T-test coefficients
disp('ESSMETUIN Coefficients (T-Test)');
disp(mdl_ess.Coefficients);
%  ANOVA table
disp('ESSMETUIN ANOVA Table');
anova(mdl_ess)

% line Graph: Percent Error vs Resistance
figure;
hold on;

% i used logarithmic scale to draw my graph

% Plot BOJACK data points and regression line
semilogx(nominals, boj_error, 'ob-', 'LineWidth', 2, 'MarkerSize', 8, 'DisplayName', 'BOJACK');
plot(nominals, predict(mdl_boj, nominals'), '--b', 'LineWidth', 1.5, 'DisplayName', 'BOJACK Fit');

% Plot ESSMETUIN data points and regression line
semilogx(nominals, ess_error, 'xr-', 'LineWidth', 2, 'MarkerSize', 8, 'DisplayName', 'ESSMETUIN');
plot(nominals, predict(mdl_ess, nominals'), '--r', 'LineWidth', 1.5, 'DisplayName', 'ESSMETUIN FIT');
set(gca, 'XScale', 'log')

% formatting
xlabel('Resistance (Ohms)');
ylabel('Average Percent Error (%)');
title('Average Percent Error vs Resistance');
legend('Location', 'northwest');
grid on;
hold off;
```