A Project entitled

Optimizing Quality and Performance Using Six Sigma Methodologies in Automotive Systems

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An Abstract of

Optimizing Quality and Performance Using Six Sigma Methodologies in Automotive Systems

This project applies Six Sigma methodologies to analyze and enhance the performance and reliability of Electric Vehicle (EV) battery systems. Using the DMAIC (Define, Measure, Analyze, Improve, Control) framework, our team examined a comprehensive EV battery dataset comprising parameters such as State of Charge (SoC), Voltage, and Temperature to identify root causes of battery faults. Statistical tools, including correlation analysis, ANOVA, capability indices (Cp, Cpk), and control charts were employed to evaluate process stability and detect performance degradation patterns. Key findings revealed that lower Voltage and SoC, coupled with rising Temperature, significantly contribute to battery faults. The process capability analysis further showed that faulty batteries had much lower Cp and Cpk values, indicating unstable and inefficient processes. Improvement recommendations include establishing real-time monitoring thresholds, implementing preventive maintenance protocols, and developing standard operating procedures to mitigate fault risks. This study demonstrates the potential of Six Sigma in advancing EV battery system quality and sets a foundation for future integration of predictive analytics and automated control mechanisms in battery manufacturing.

Keywords:

Six Sigma, statistical analysis, correlation analysis, DMAIC, ANOVA fault detection, real-time monitoring;

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1. Introduction

In the last few years, electric vehicles have become more popular across the world. Because of the rise in petrol and diesel prices and the increasing concern about air pollution, many governments and companies are promoting EVs. EVs are also good for the environment and reduce fuel costs for the users. But even with all the advantages, there are still some major challenges in the EV industry. One of the most common and serious problem is the battery performance. The battery is the heart of the electric vehicle. If the battery fails or gives low performance, the vehicle cannot run properly and may even stop in between. Also, battery replacement is very costly, and faults in the battery can lead to customer complaints, safety issues and loss to the company.

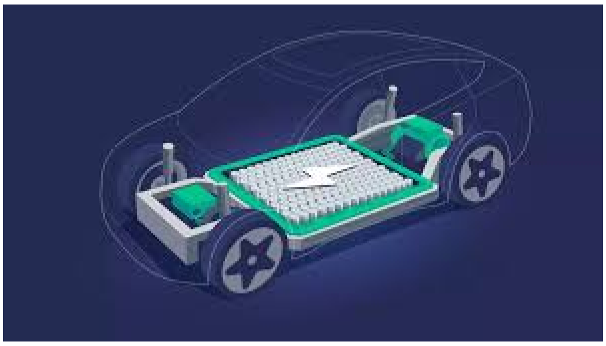

Figure1-1: EV Battery Pack

This is the reason many automobile companies are now focusing more on improving battery systems. They want to reduce the number of faults, improve reliability and increase battery life. One of the proven methods used in the industry for this is Six Sigma. It is a process improvement method that helps to reduce variation, remove defects and improve product quality. It gives a step-by-step approach to understand what is going wrong in the process and how to fix it. Many big companies like Toyota, Ford, and General Motors are already using Six Sigma in their production lines to improve quality and reduce waste. It is also helpful in solving problems related to EV battery systems.

For this reason, we decided to work on a Six Sigma based project where we can study EV battery behavior, understand the reason for failures, and give some useful suggestions for improvement. We used the DMAIC method (Define, Measure, Analyze, Improve, Control), which is the standard Six Sigma process used for solving problems. The study mainly focused on finding which factors affect battery health and how these faults can be reduced using simple data and analysis tools.

1.1. Research Scope

This study focused on analyzing a real-world EV battery dataset using Six Sigma methodology. The dataset included three important parameters: Voltage, Temperature, and State of Charge (SOC). These values are directly related to battery performance and can help in identifying when a fault is likely to happen.

We applied the DMAIC approach for this project. In the Analyze phase, we used Excel and Minitab software to perform correlation analysis, boxplots, ANOVA tests, and Cp/Cpk calculations. Our findings helped us to identify patterns in the battery data and understand how the values change during the battery discharge cycle. Based on this, we suggested practical actions to monitor and control battery faults before they become serious problems.

2. Literature Review

Paper 1: Using DMAIC Method in Indian Manufacturing Company

This paper was about how Six Sigma DMAIC method was used in an Indian company which was making rubber weather strips for automobile industry. This organization faced the problem of high rejection rate of 5.5%. Because of this, they were facing material loss and also complaints from the customer side. So, the authors decided to solve this using DMAIC method. In the define phase, they defined what the problem is, and what data is needed. In the measure phase, they collected rejection data from the last few months. In the analyze phase, they used Pareto charts, fishbone diagrams and control charts to find the main reasons of rejection. After that in improve they standardized process, gave training to workers and checked machine settings also. Then in control phase they started regular monitoring with control chart and inspection checks.

After all these steps, rejection got reduced from 5.5% to 3.08%. Sigma level also improved and the company saved around ₹15,000 monthly (Mittal et al., 2023).

We used this paper because it showed us a real example of how DMAIC works in a step-wise method. This helped us plan our own EV battery fault project. We also used some same tools like control chart, pareto and Cp-Cpk for analysis.

Paper 2: Systematic Review on EV and Decision Making Using MCDM Methods

In this paper, we studied how electric vehicles research is growing and how researchers are using MCDM (Multi Criteria Decision Making) tools to solve complex problems in the EV sector. The authors focused on articles which talked about EV-related decision making, like where to put charging stations, which batteries to select, or what the top challenges in EV development are. They used a special review method called SLR (Systematic Literature Review) and for ranking the articles, they used two tools called AHP (Analytical Hierarchy Process) and TOPSIS. With this, they analyzed 73 top articles and ranked them based on how much impact they had.

The main finding of the paper was that many researchers were focusing more on EV charging station location and EV component selection. Battery-related studies were also high. They said that MCDM tools helped in comparing different choices and selecting best option when many factors are there.

This paper helped us understand how MCDM and data analysis is getting used in EV research. It gave us motivation to use structured methods in our project and how decision tools can help in finding faults and improving battery process (de Oliveira et al., 2024).

Paper 3: Big Data Based Battery Fault Detection for EV

This paper talked about how big data can be used to find battery faults in electric vehicles. The authors collected battery voltage data from the Beijing Electric Vehicles Data Centre. They focused on 91 battery cells which were in the same battery pack, and data was recorded every 10 seconds. They used the 3r-MSS method which was based on the Gaussian distribution, to remove abnormal data and find out where the faults are coming from. After that, they used a BP neural network and other methods like LOF and clustering to cross-check the results.

They also checked how faults are changing with time and under different outside conditions like temperature. The main result was that even if battery voltage looks normal, there can be a hidden problem inside which can be found using this model. They also said that this type of fault finding can help in better battery design in future.

We used this paper because it gave us the idea that even simple voltage data can show early signs of failure. It helped us in doing analysis using box plots, Cp Cpk, and control charts in our own battery fault project (Zhao et al., 2017).

Paper 4: Review on Fault and Defect Diagnosis of Lithium-Ion Battery for EVs

This paper talked about how big data can be used to find battery faults in electric vehicles. This paper gave a full review on how lithium-ion battery fails in electric vehicles and what methods are used to detect the faults. The authors said the battery is the main part in EV and if it faces faults like overheating, overcharging or short circuit, then it could be dangerous. The paper first explained two types of faults, one is progressive which happens slowly over time such as capacity drop, and the second is sudden faults like short circuit or thermal runaway. They also discussed system faults like BMS failure, sensor problems and loose connections.

They talked about four main types of fault diagnosis methods: model-based, data-driven, knowledge-based and statistical methods. Each method had some advantages and disadvantages. The paper also showed what the challenges are in diagnosing faults because sometimes two faults look similar. They said that early warning systems are very important so that critical battery problems can be stopped before they happen.

We used this paper as it showed us different types of battery faults which can happen during real driving conditions. It also showed that the same type of faults can happen for many reasons, so we have to study the data properly. This was helpful for our project because we also considered voltage, SOC and temperature values to find battery faults (Zou et al., 2023).

3. Problem Statement and Objectives of the Study

In electric vehicles, battery problems are one of the most serious issues. If the battery fails or is low on performance, it can cause safety issues, a poor driving experience and also higher costs for the user. Most of the time, the fault happens because of voltage drops, very high temperatures or a low state of charge. But in real-world driving conditions, it is not easy to find when the battery will fail. This is a critical problem for EV companies because batteries are expensive and if many customers face problems, they can lose trust in the company.

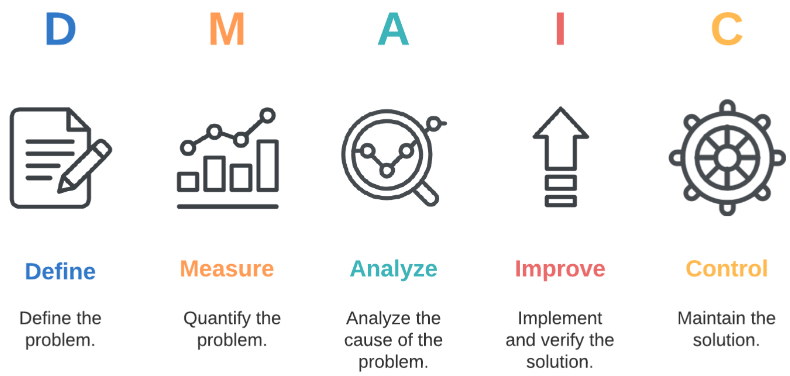

Figure 3-1: DMAIC

In this project, our main objective was to study how the battery behaves during usage and how the values change before it becomes faulty. We followed the Six Sigma method called DMAIC to do the project step by step. We checked how voltage, SOC and temperature are related to battery health. We used Excel and Minitab to analyze box plots, correlation, Cp-Cpk and ANOVA. After that, we gave some suggestions which can help to reduce battery faults and improve quality and safety. This study can help companies to take better decisions and reduce the failure in real battery systems.

4. Methodology

The Six Sigma DMAIC approach was used in this project to find and fix issues with EV batteries. Using Excel and Minitab, a dataset of 728 samples was examined. Each sample had SOC, Voltage, Temperature, and a binary fault label. Initial study of the discharge cycle revealed that the voltage continuously dropped and the temperature abruptly increased as the state of charge (SOC) decreased. This behavior is typical of battery degradation. With a temperature rise of ~971.1 K/h and a voltage drop of ~6.97 V/h, performance metrics measured this trend.

ANOVA statistical study verified that there was a significant difference between healthy and defective batteries in terms of voltage, SOC, and temperature. Voltage was the most sensitive parameter, displaying the greatest F-statistic. These results were corroborated by boxplots and correlation analysis, which showed that these characteristics and fault risk were strongly correlated.

Process capability study revealed that whereas defective batteries had considerably lower values (e.g., Cpk = 0.41 for Temperature), showing considerable variability and defect risk, healthy batteries had Cp and Cpk values close to 1, indicating effective process control. While highlighting persistent fault rates, control charts (X-bar and P-charts) verified statistical consistency.

Every step of the DMAIC process was methodically carried out: Define the goal, Data preparation was required for the measure. Examine statistical tools to determine important variables. Enhance SOP updates and suggested real-time monitoring thresholds. To guarantee long-term stability, control training and charts. Clear insights and workable solutions to improve EV battery reliability were offered by this methodical approach.

5. Data Analysis, Results, and Discussion

This section presents a detailed walkthrough of each phase of DMAIC as applied to the EV battery dataset, with a focus on identifying key fault contributors and proposing data-driven solutions. Various statistical tools such as correlation analysis, boxplots, ANOVA, and process capability (Cp, Cpk) studies were used to uncover patterns in the data and evaluate process performance. The following subsections describe the complete DMAIC process and highlight the findings that guided improvement strategies.

5.1. Define Phase: Understanding the Problem

In the Define phase of this Six Sigma project, the goal was to reduce battery faults in electric vehicles (EVs) by identifying the root causes of poor performance. The goal was to improve battery quality and reliability through reductions in faulty units. High variability of primary parameters Voltage, State of Charge (SOC), and Temperature was identified through analysis, which was linked with increased battery faults. The dataset used contained 728 samples with SOC (%), Temperature (Kelvin), and Voltage (Volts) as the features, which were labeled as healthy (0) or defective (1). The primary stakeholders included battery makers, automotive associations, quality control teams, and EV system engineers who were seeking to offer safer and more dependable EV performance.

5.2. Measure Phase: Collecting and Understanding Data

At the Measure stage, data from 728 EV battery records were collected and preprocessed in order to identify the type and distribution of key performance parameters. The data set was balanced with 50% healthy and 50% failed samples to provide an unbiased evaluation. Measured parameters included State of Charge (SOC) in percentage, Voltage in volts, and Temperature in Kelvin. Descriptive statistics for the mean, maximum, and minimum values were calculated to grasp parameter behavior in the two classes. The process gave a good statistical foundation for the detection of patterns indicative of battery faults.

5.3. Analyze Phase: Understanding the Root Causes of Faults

The Analyze phase is a crucial part of the DMAIC methodology, where we examine the collected data to identify the actual causes behind the observed problems in this case, the faults in electric vehicle (EV) batteries. Various statistical tools and visualization techniques were used to carefully study the relationships between key battery parameters like State **of Charge (SOC)**, **Voltage**, and **Temperature** and the health status of the battery (healthy or faulty). These analyses helped us understand how each factor contributes to faults and how significantly they influence battery performance. The purpose of this phase was to pinpoint which variables were most responsible for battery failures and to prepare for targeted improvements.

5.3.1. Descriptive Statistics

A descriptive statistical review of the EV battery dataset was done to grasp the behavior of important parameters SOC, voltage, and temperature across both healthy and defective batteries before doing advanced studies. Particularly in faulty samples, the results revealed clear fluctuation, particularly with regard to average voltage and a larger range, suggesting possible instability. This fundamental realization underlined the need of more research.

SOC		*Temperature*		*Voltage*	
Mean	43.50226	Mean	357.3408464	Mean	3.34295542
Standard Error	1.319211	Standard Error	1.549711306	Standard Error	0.012871819
Median	45.86389	Median	348.3602327	Median	3.384623732
Mode	100	Mode	298.15	Mode	#N/A
Standard Deviation	35.59427	Standard Deviation	41.81349706	Standard Deviation	0.347300656
Sample Variance	1266.952	Sample Variance	1748.368536	Sample Variance	0.120617746
Kurtosis	-0.62919	Kurtosis	0.257696705	Kurtosis	-0.670934044
Skewness	-0.36731	Skewness	0.834663879	Skewness	-0.424485936
Range	151.0211	Range	190.7120378	Range	1.376875214
Minimum	-51.0211	Minimum	298.15	Minimum	2.642464786
Maximum	100	Maximum	488.8620378	Maximum	4.01934
Sum	31669.64	Sum	260144.1362	Sum	2433.671546
Count	728	Count	728	Count	728

Table 5-1: Descriptive Statistics

5.3.2. Correlation Analysis

Battery characteristics and fault occurrence were evaluated using correlation analysis. While Temperature exhibited a modest positive correlation (0.40), Voltage had a modest negative correlation (-0.39), SOC and faults showed a mild negative association (-0.28). Furthermore, substantially positively connected were SOC and voltage (0.95); nevertheless, voltage and temperature displayed a strong negative connection (-0.91). These results found Temperature to have a little influence whereas Voltage and SOC were found as main markers of problems.

CORRELATION	
SOC vs Label	-0.28093
Temp vs Label	0.401794
Volt vs label	-0.39225
SOC vs Temp	-0.84252
SOC vs Volt	0.957181
Volt vs Temp	-0.91216

Table 5-2: Correlation Analysis

5.3.3. Boxplot Analysis

Boxplots for every parameter across both good and defective batteries were developed to bolster these observations. Along with greater and more erratic temperature readings, faulty batteries displayed lower SOC and voltage levels. These visual trends validated SOC, Voltage, and Temperature as effective early markers of battery failures and strengthened the statistical results.

Figure 5-1: Boxplots

5.3.4. ANOVA Analysis

An ANOVA test was performed to assess the influence of critical battery parameters—State of Charge (SOC), Temperature, and Voltage—on battery health by contrasting healthy and defective groups. The null hypothesis (H_0) posited no significant difference between group means, whereas the alternative hypothesis (H_1) indicated that at least one parameter significantly influences battery condition. Utilizing a significance level of $\alpha = 0.05$, the study determined that all three variables were statistically significant.

Voltage exhibited the most significant impact, evidenced by a high F-statistic and a p-value < 0.001, establishing it as the most influential parameter. SOC was significant at $p < 0.05$, and Temperature at $p < 0.01$, so affirming their pertinence to battery malfunctions. Boxplots visually corroborated these findings, indicating that faulty batteries typically exhibited reduced State of Charge (SOC) and Voltage, and elevated Temperature readings.

Furthermore, variability analysis indicated that healthy batteries exhibited greater stability in all metrics. Conversely, defective batteries demonstrated heightened variability particularly in Voltage and Temperature underscoring augmented process instability. These findings correspond with Six Sigma principles, highlighting the necessity of minimizing variation to guarantee quality and reliability.

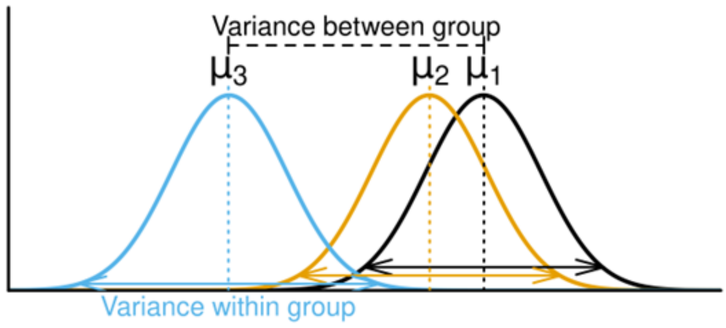

Figure 5-2: ANOVA Analysis

Relationships between factors were further investigated using correlation analysis. There was a significant negative correlation between temperature and voltage (r = -0.9122), a strong negative correlation between temperature and soC (r = -0.8425), and a very strong positive correlation between voltage and soC (r = +0.9572). Temperature had a moderately positive connection (r = +0.4018) with fault labels, whilst Voltage and SoC had a moderately to weakly negative association (r = –0.3922 and –0.2809). These trends imply that low voltage and SoC and high temperature increase the likelihood of malfunctions. The significance of these quantities in predictive monitoring systems is supported by the inverse relationship between temperature and voltage, which may represent underlying degradation mechanisms.

Dataset	Feature	F-Statistic	p-value	Significant?
Simple Classification	SOC	62.20	1.14e-14	✅ Yes
Simple Classification	Temperature	139.77	1.28e-29	✅ Yes
Simple Classification	Voltage	132.01	3.44e-28	✅ Yes
Multiple Classification	SoC	730.91	1.64e-205	✅ Yes
Multiple Classification	Temperature	806.04	1.79e-219	✅ Yes
Multiple Classification	Voltage	20587.26	0.0	✅ Yes

Figure 5-3: ANOVA Results Summary

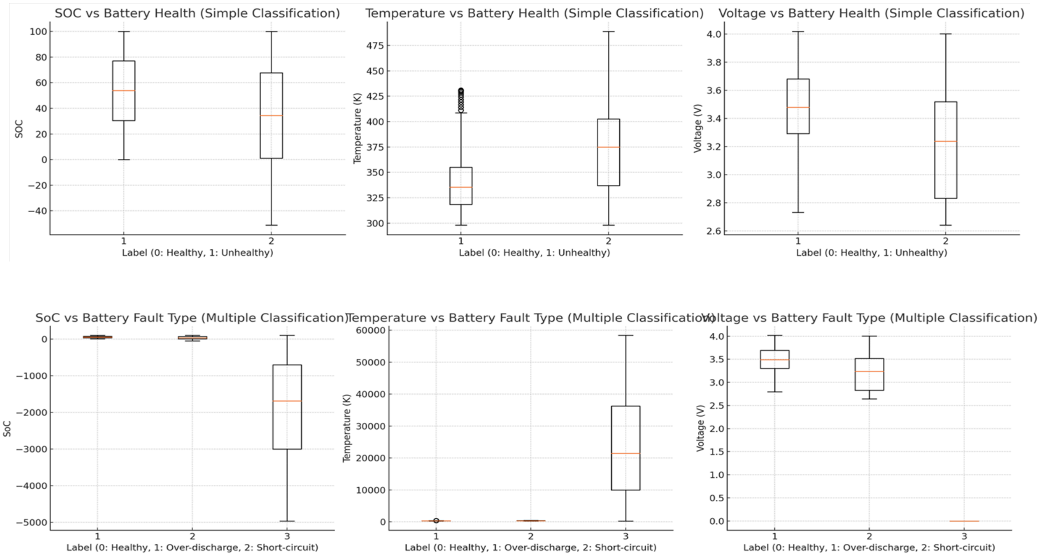

Figure 5-4: Box Plots

5.3.5. Battery Discharge Behavior and Performance Metrics Analysis

The performance of electric vehicle (EV) batteries during the discharge cycle is significantly affected by three interconnected factors: State of Charge (SoC), voltage, and temperature. Data was organized in descending sequence from 100% to 0% State of Charge (SoC) to replicate a complete discharge situation. A distinct voltage reduction was noted over time, commencing at 4.0193 V and concluding at 2.7816 V. The decline became markedly more pronounced at reduced state of charge levels, illustrating the characteristic discharge behavior of lithium-ion batteries. This trend underscores the necessity for real-time monitoring to avert deep discharge, which might diminish performance and jeopardize battery safety.

A significant temperature increase was observed from 298.15 K to 470.57 K. The swift increase in temperature indicates significant thermal stress during discharge, emphasizing the necessity of incorporating effective thermal management measures in battery design. Excessive heat can expedite cell breakdown, diminish battery lifespan, and heighten the risk of thermal runaway, especially in densely arranged battery systems.

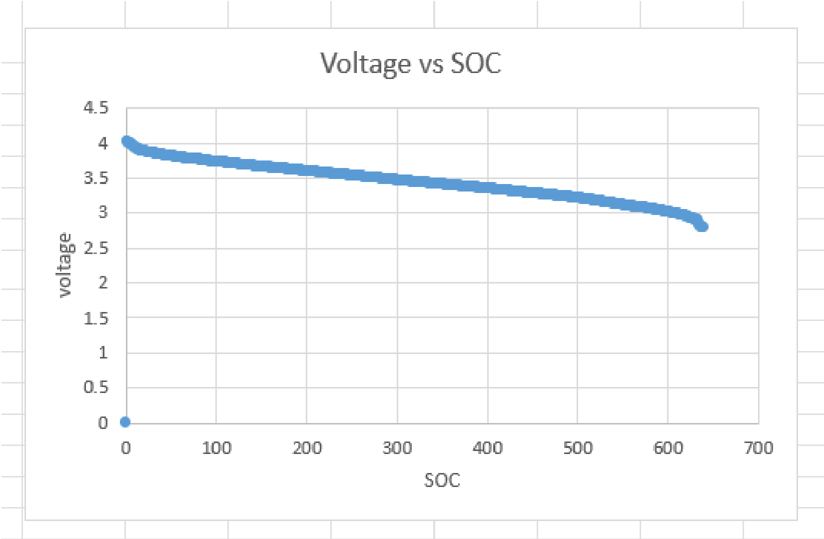

Figure 5-5: Voltage vs SOC graph

Various significant performance measures were computed to quantify these effects. The voltage decline rate was ascertained to be roughly 6.97 V/hour, whilst the temperature escalation rate was a concerning 971.1 K/hour. Furthermore, the voltage decreased below the critical threshold of 3V within 600 seconds of discharge, a level recognized to affect the long-term health and efficiency of battery cells.

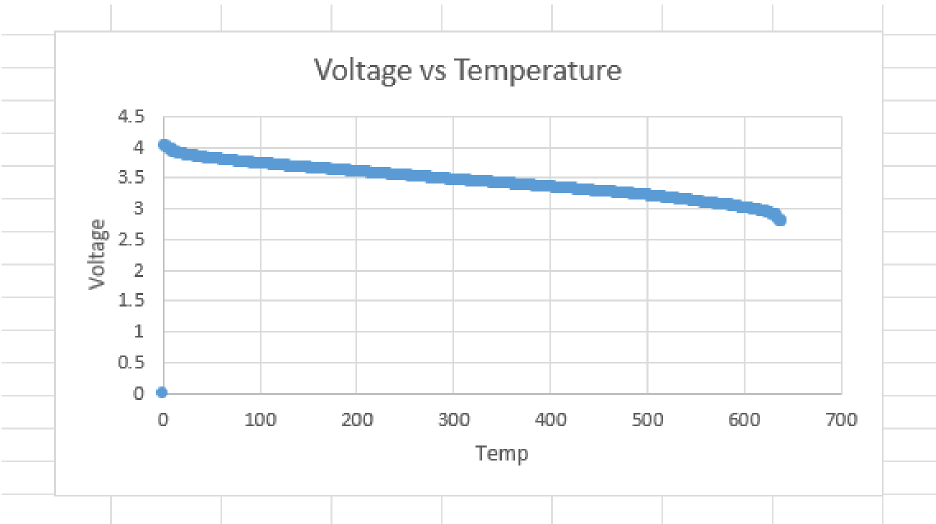

Figure 5-6: Voltage vs Temperature Graph

These observations validate that state of charge, voltage, and temperature are dynamic, interrelated markers of battery health and performance. Their conduct during discharge offers critical insights for early defect identification and predictive maintenance. The results also endorse the establishment of secure operational thresholds and real-time control systems, consistent with Six Sigma principles aimed at reducing variation, enhancing reliability, and guaranteeing quality in electric vehicle battery systems.

5.3.6 Statistical Analysis of Process Capability

The performance of electric vehicle (EV) batteries is crucial for safety, efficiency, and user pleasure. This study assesses the process capability of two essential parameters temperature and voltage directly associated with range loss, overheating, and deterioration. The aim is to utilize Cp and Cpk indices to evaluate the consistency of these parameters within acceptable design limits throughout the production and testing of lithium-ion batteries. The technique employs a labeled dataset in which batteries are classified as either functional or defective. Specification limitations were established from the healthy battery cohort utilizing the Six Sigma methodology (mean ± 3 standard deviations), and these limits were similarly applied to the defective group to maintain a uniform benchmark. Temperature (in Kelvin) and voltage (in Volts) were selected because of their significant impact on battery health and system reliability.

Preliminary computations for Cp and Cpk were conducted in Microsoft Excel to assess process variation and alignment. Excel was utilized for initial analysis, but Minitab was applied for validation and more profound statistical insights. Minitab's instruments such as capability histograms, I-MR control charts, and normal probability plots offered visual validation of process stability and variability.

The results elucidated discrepancies between functional and defective batteries, uncovering prospects for improving dependability and minimizing defects. This analysis bolsters Six Sigma quality objectives by providing a data-driven methodology for enhancing battery performance and production standards within the electric vehicle sector.

Parameter	Cp (Excel)	Cpk (Excel)	Cp (Minitab)	Cpk (Minitab)	Interpretation
Temperature	1	1	≈19.55	≈19.55	Excellent control, highly centered
Voltage	≈1.00	≈1.00	High	High	Well-controlled and consistent

Table 5-3: Healthy Batteries: Stable and Capable Process

The healthy battery group demonstrated robust process control for both parameters. The Cp and Cpk values of approximately 1.00 in Excel, along with extremely high values in Minitab, indicate that the process is not only capable of operating within specification but does so with minimal variation. The near-perfect centering between USL and LSL signifies a statistically stable process, minimizing risk of defects. Such consistency is critical in the automotive domain where reliability, safety, and customer trust are directly impacted by battery quality.

Parameter	Cp (Excel)	Cpk (Excel)	Cp (Minitab)	Cpk (Minitab)	Interpretation
Temperature	≈0.65	≈0.41	≈13.19	≈8.21	High variability, process mean shifted
Voltage	≈0.68	≈0.44	Low	Low	Below capable levels, inconsistent control

Table 5-4: Healthy Batteries: Stable and Capable Process

In contrast, the faulty battery group showed poor process capability and centering, with Cp and Cpk values well below the acceptable threshold of 1.0. Voltage values, in particular, revealed high variability and unstable control. The temperature process was significantly shifted toward the upper specification limit, indicating overheating tendencies. These results suggest a non-capable process with an elevated risk of producing defective batteries, potentially leading to field failures, customer complaints, and increased warranty claims in the automotive market.

5.4 Improve Phase: Implementing Data-Driven Solutions

Once root causes of battery faults were identified, the improvement phase focused on developing practical and data-driven solutions to reduce defects and enhance battery reliability. Our goal was to translate the insights from the Analyze phase into actionable steps that can be implemented in the battery production and monitoring process.

5.4.1. Threshold-Based Alerts for Early Warning

Threshold-based notifications were established for critical battery characteristics to avert malfunctions. A voltage threshold of 3.5V and a state of charge (SoC) threshold of 30% were established based on fault-prone circumstances in the dataset. A maintenance alarm should be activated if the voltage falls below 3.5V. Likewise, if the State of Charge (SoC) drops below 30%, the system must prompt for recharging or inspection. These levels serve as preliminary indicators to improve safety and battery dependability.

5.4.2. A Sample Standard Operating Procedure (SOP) for Fault Prevention

To ensure prompt and consistent responses to critical battery conditions, a Standard Operating Procedure (SOP) was established. The objective is to enable early detection and timely action based on predefined thresholds for State of Charge (SOC) and voltage. The system continuously monitors SOC, voltage, and temperature using real-time sensors. If the voltage drops below 3.5V, an alert is triggered, and maintenance is scheduled within 24 hours. If SOC falls below 30%, the user is notified to recharge, and the event is logged for trend analysis. In cases where three or more threshold alerts occur within a week, a manual inspection is required. All actions and interventions are recorded in the system log, and battery performance is reviewed weekly, with a report submitted to the QA team. The SOP is reviewed and updated quarterly to reflect evolving data trends and operational needs.

5.4.3. Real-Time Dashboard Implementation

Another important recommendation is the development of real-time dashboards for visualizing live battery health data. These dashboards should display Voltage, SOC, and Temperature in a user-friendly format with color-coded warnings. For instance, green for normal range, yellow for warning zone, and red for critical values. Integration with cloud-based systems or vehicle control units can allow centralized monitoring across fleets. These dashboards help operators and engineers take immediate action when a battery is approaching failure conditions.

5.5 Control Phase: Sustaining Improvements and Reliability

The Control phase is the concluding and continuous step in the DMAIC approach, designed to ensure that introduced changes sustain their effectiveness over time. In electric vehicle battery systems, it is essential to regulate critical parameters voltage, state of charge, and temperature to ensure dependability and minimize failure rates. X-bar and R charts were employed to monitor the mean and variability of continuous parameters. These charts facilitate the identification of deviations or trends that indicate possible problems, necessitating fast remedial measures when values exceed control limits.

It is advisable to conduct daily evaluations of control charts and weekly summary reports on fault trends for consistent monitoring. A designated quality engineer must oversee these metrics and address any threshold infringements. Given that battery performance may fluctuate due to design modifications or environmental influences, it is imperative to regularly revise thresholds and process baselines to align with prevailing conditions.

To guarantee compliance, periodic internal audits must evaluate data precision, response durations, and conformity to standard operating procedures. A feedback loop must be established to enable insights from the Control phase to inform preceding stages of DMAIC, such as data re-analysis or SOP revision. This ongoing monitoring and reporting system facilitates enduring enhancements and fosters a culture of quality and dependability.

6. Conclusion and Future Research

This project helped us to understand how simple analysis using Six Sigma methods can give useful results in real battery systems. After doing all the analysis, we saw that voltage and SOC were going down together and at the same time temperature was increasing during battery discharge. Faulty batteries had more variation and higher temperatures, while healthy ones were more stable. ANOVA test showed that voltage had the most effect on battery condition, followed by temperature and SOC. Cp and Cpk values were good in healthy batteries but very low in faulty ones, which showed that faulty batteries were not under control.

Based on these findings, we gave suggestions like using threshold alerts and real-time dashboards to catch early warning signs. A sample SOP was also made to take quick action when the voltage or SOC drops.

For future work, we can use more battery parameters like charging cycles, current, and ambient temperature. Machine learning models can also be used to predict faults early. Real-time testing on EVs will also help to know how our ideas work in practical conditions. These things will help to improve battery life and reduce risks in electric vehicles.

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Appendices

Appendix 1.1 ANOVA

SOC_SIMPLE

One-way ANOVA: C1, 0, 1

Method

Null hypothesis	All means are equal
Alternative hypothesis	Not all means are equal
Significance level	α = 0.05
Rows unused	728

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	3	C1, 0, 1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	2	37345765	18672882	822.16	0.000
Error	1453	33000685	22712		
Total	1455	70346450			

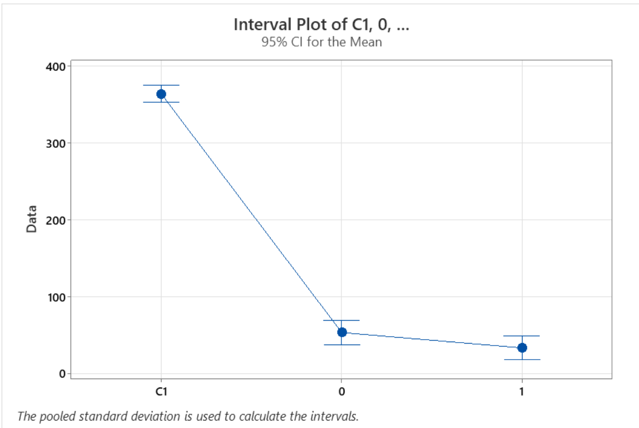
Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
150.705	53.09%	53.02%	52.96%

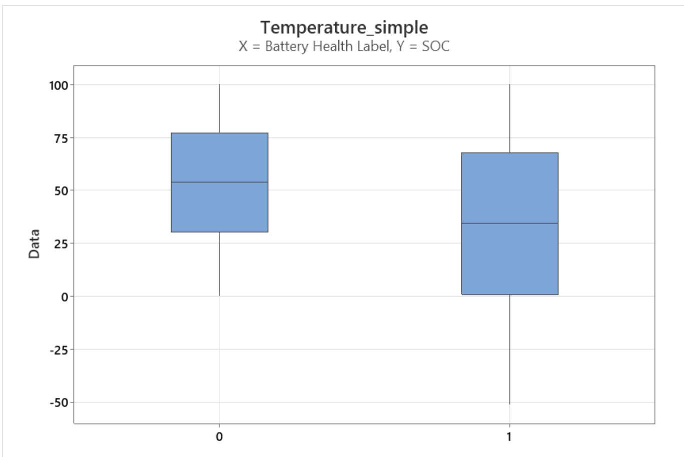
Means

Factor	N	Mean	StDev	95% CI
C1	728	363.50	210.30	(352.54, 374.46)
0	364	53.49	27.46	(38.00, 68.99)
1	364	33.51	39.79	(18.01, 49.00)

Pooled StDev = 150.705



One-way ANOVA SOC Simple



Boxplot

TEMPERATURE_SIMPLE

One-way ANOVA: C1, 0, 1

Method

Null hypothesis	All means are equal
Alternative hypothesis	Not all means are equal
Significance level	α = 0.05
Rows unused	728

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	3	C1, 0, 1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	2	219007	109503	4.79	0.008
Error	1453	33218167	22862		
Total	1455	33437174			

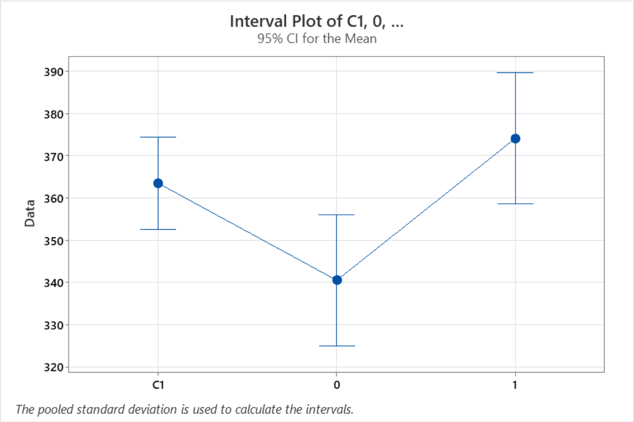
Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
151.201	0.65%	0.52%	0.37%

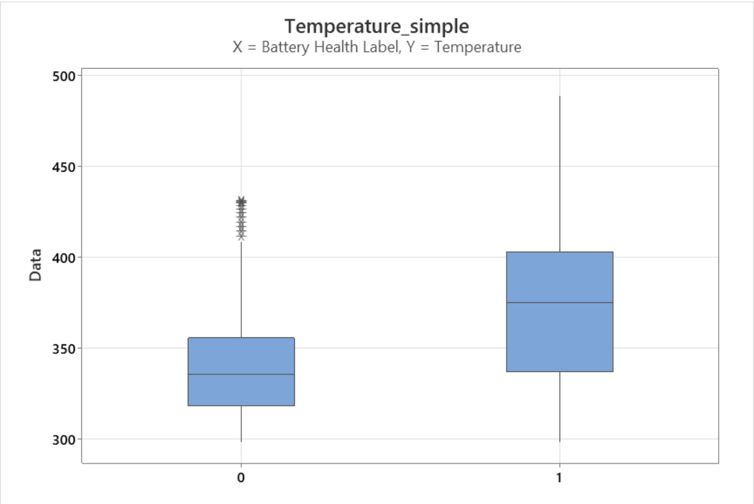
Means

Factor	N	Mean	StDev	95% CI
C1	728	363.50	210.30	(352.51, 374.49)
0	364	340.55	29.67	(325.01, 356.10)
1	364	374.13	45.34	(358.58, 389.68)

Pooled StDev = 151.201



One-way ANOVA Temperature Simple



Boxplot Temperature Simple

VOLTAGE_SIMPLE

One-way ANOVA: C1, 0, 1

Method

Null hypothesis	All means are equal
Alternative hypothesis	Not all means are equal
Significance level	α = 0.05
Rows unused	728

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	3	C1, 0, 1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	2	47215581	23607790	1066.86	0.000
Error	1453	32152376	22128		
Total	1455	79367957			

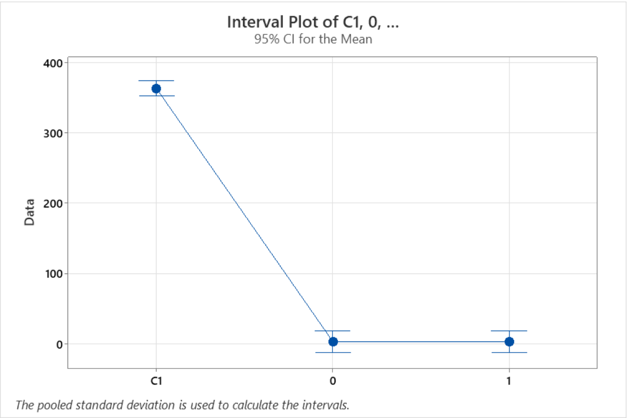
Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
148.756	59.49%	59.43%	59.38%

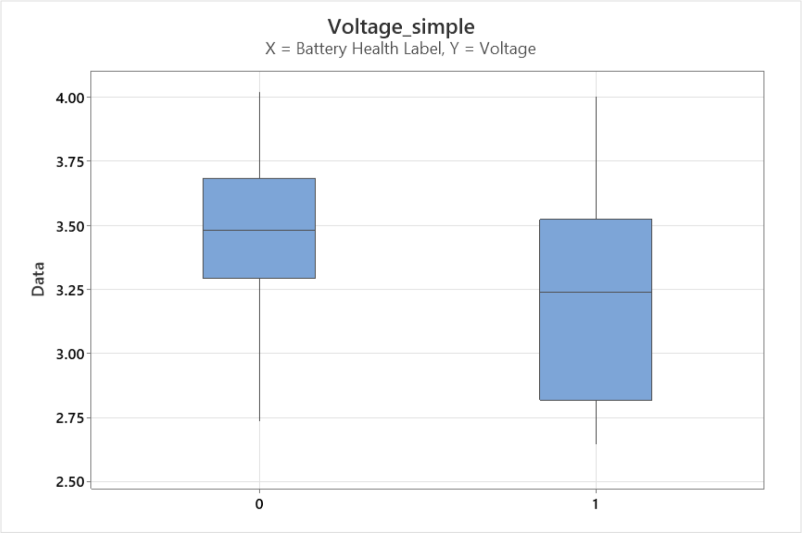
Means

Factor	N	Mean	StDev	95% CI
C1	728	363.50	210.30	(352.69, 374.31)
0	364	3.4791	0.2564	(-11.8153, 18.7735)
1	364	3.2068	0.3724	(-12.0876, 18.5012)

Pooled StDev = 148.756



one-way ANOVA Voltage Simple



Boxplot Voltage Simple

SOC_MULTIPLE

One-way ANOVA: C1, 0, 1

Method

Null hypothesis	All means are equal
Alternative hypothesis	Not all means are equal
Significance level	α = 0.05
Rows unused	1516

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	3	C1, 0, 1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	2	132460454	66230227	999.83	0.000
Error	1937	128310003	66242		
Total	1939	260770458			

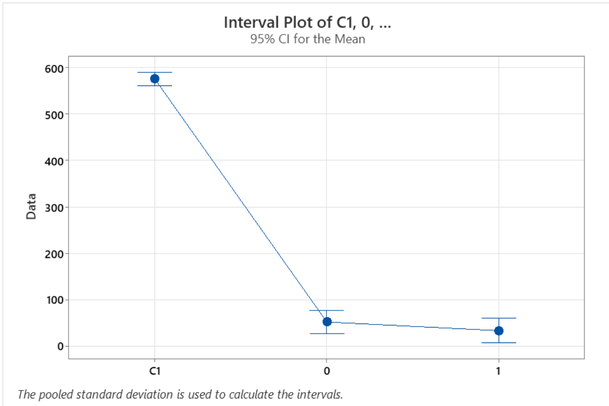
Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
257.374	50.80%	50.75%	50.71%

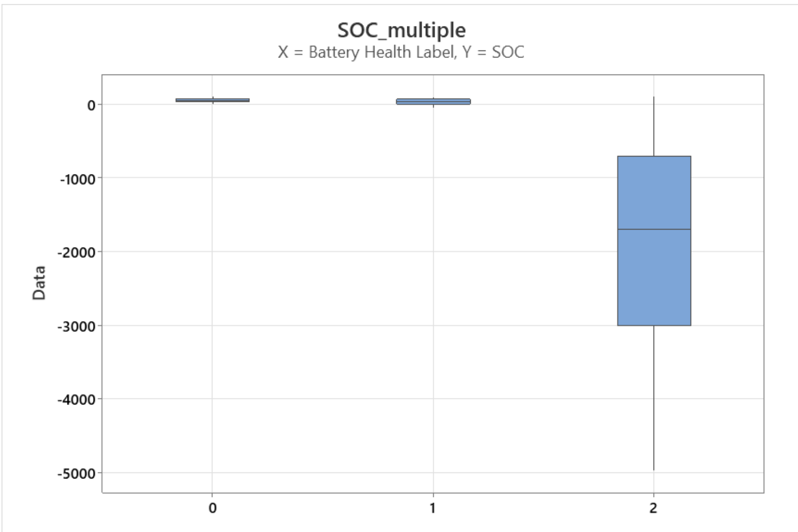
Means

Factor	N	Mean	StDev	95% CI
C1	1152	575.50	332.70	(560.63, 590.37)
0	424	52.23	28.08	(27.72, 76.75)
1	364	33.51	39.79	(7.05, 59.97)

Pooled StDev = 257.374



One-way ANOVA SOC Multiple



Boxplot SOC multiple

TEMPERATURE_MULTIPLE

One-way ANOVA: C1, 0, 1

Method

Null hypothesis	All means are equal
Alternative hypothesis	Not all means are equal
Significance level	α = 0.05
Rows unused	1516

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	3	C1, 0, 1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	2	23190288	11595144	174.85	0.000
Error	1937	128450319	66314		
Total	1939	151640607			

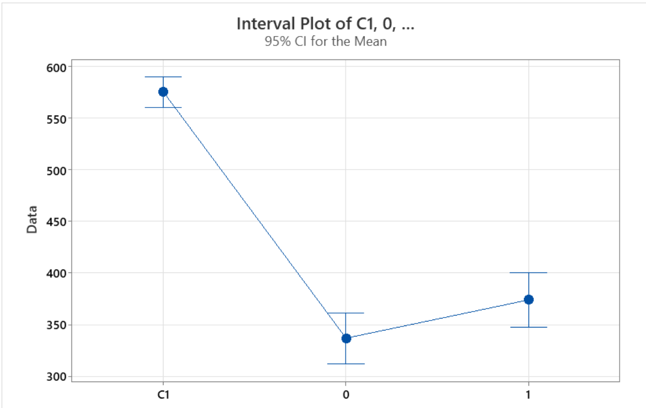
Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
257.515	15.29%	15.21%	15.14%

Means

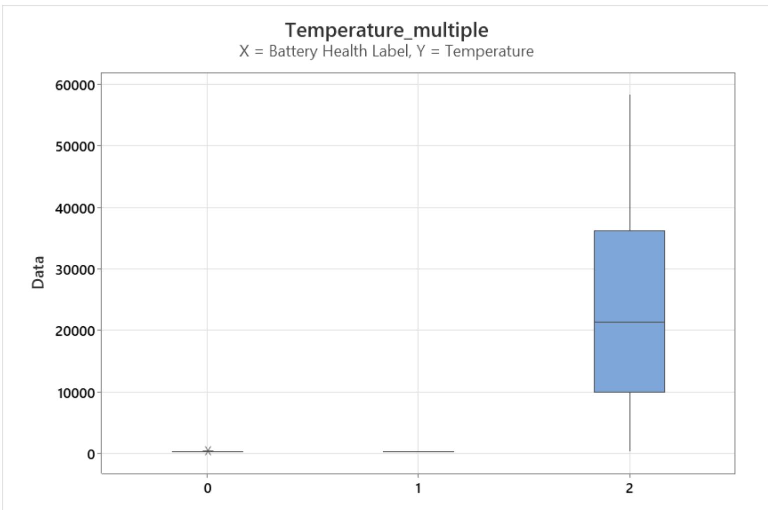
Factor	N	Mean	StDev	95% CI
C1	1152	575.50	332.70	(560.62, 590.38)
0	424	337.05	26.72	(312.52, 361.57)
1	364	374.13	45.34	(347.66, 400.60)

Pooled StDev = 257.515



The pooled standard deviation is used to calculate the intervals.

one-way ANOVA Temperature multiple



Boxplot Temperature multiple

VOLTAGE_MULTIPLE

One-way ANOVA: C1, 0, 1

Method

Null hypothesis	All means are equal
Alternative hypothesis	Not all means are equal
Significance level	α = 0.05
Rows unused	1516

Equal variances were assumed for the analysis.

Factor Information

Factor	Levels	Values
Factor	3	C1, 0, 1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	2	153173008	76586504	1164.41	0.000
Error	1937	127401967	65773		
Total	1939	280574974			

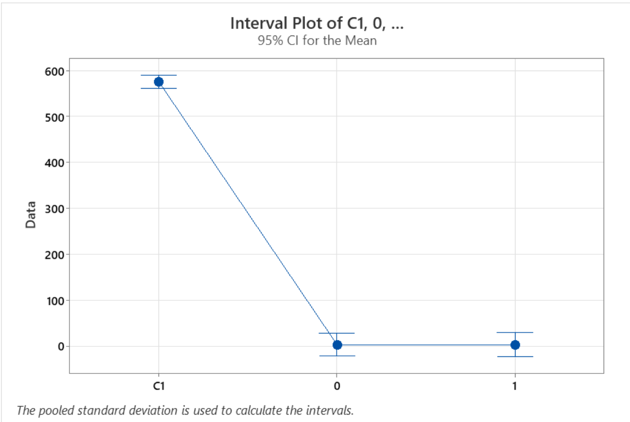
Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
256.462	54.59%	54.55%	54.51%

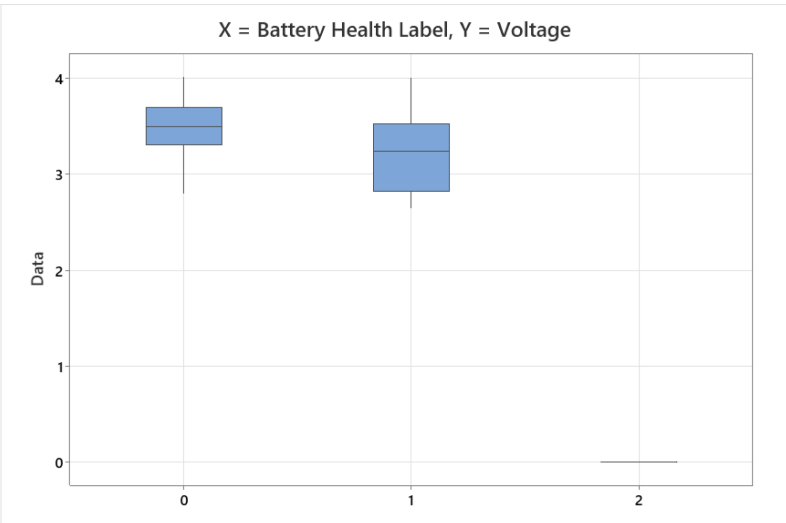
Means

Factor	N	Mean	StDev	95% CI
C1	1152	575.50	332.70	(560.68, 590.32)
0	424	3.4908	0.2597	(-20.9357, 27.9172)
1	364	3.2068	0.3724	(-23.1560, 29.5697)

Pooled StDev = 256.462



One-way ANOVA Voltage Multiple



Boxplot Voltage Multiple

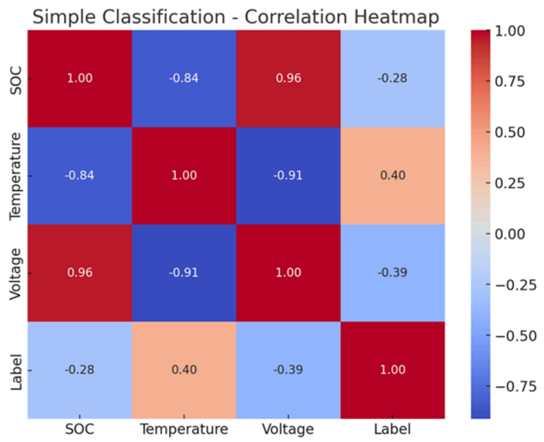
	SOC	SOC	SOC	Temperature	Temperature	Temperature	Voltage	Voltage	Voltage
	mean	std	CV	mean	std	CV	mean	std	CV
Label									
0	53.49475	27.46277	0.513373	340.5519812	29.66752576	0.087115998	3.47909	0.25642	0.073703
1	33.50977	39.78618	1.187301	374.1297116	45.34431011	0.121199436	3.206821	0.372356	0.116114

Simple Classification variability Metrics

	SoC	SoC	SoC	Temperature	Temperature	Temperature	Voltage	Voltage	Voltage
	mean	std	CV	mean	std	CV	mean	std	CV
Label									
0	52.23497	28.07908615	0.537553409	337.046559	26.7226636	0.079284784	3.490761	0.259722	0.074403
1	33.50977	39.78618203	1.187301002	374.1297116	45.34431011	0.121199436	3.206821	0.372356	0.116114
2	-1922.67	1442.915115	-0.750475703	23889.77815	16455.96352	0.688828646	0	0	

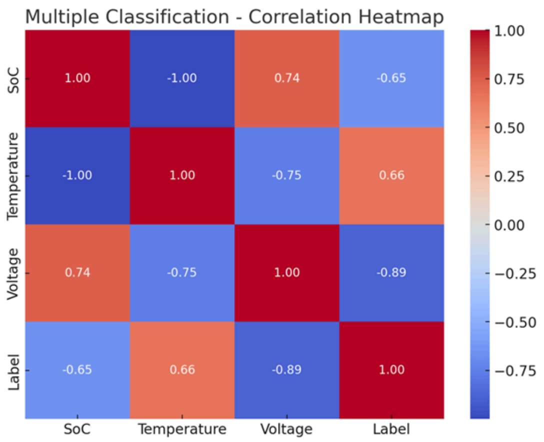
Multiple Classification variability Metrics

	SOC	Temperature	Voltage	Label
SOC	1	-0.842520843	0.95718052	-0.280926118
Temperature	-0.84252	1	-0.912155662	0.401793896
Voltage	0.957181	-0.912155662	1	-0.392247476
Label	-0.28093	0.401793896	-0.392247476	1



Correlation Analysis - Simple Classification

	SoC	Temperature	Voltage	Label
SoC	1	-0.999460559	0.74007083	-0.651353977
Temperature	-0.99946	1	-0.751943369	0.662471745
Voltage	0.740071	-0.751943369	1	-0.888890224
Label	-0.65135	0.662471745	-0.888890224	1



Correlation Analysis - Multiple Classification