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Article

Variability in initial battery cell characteristics and its implications for manufacturing quality control

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ABSTRACT

Ensuring manufacturing consistency in lithium-ion batteries is critical for reliable performance, safety, and longevity. This study examines the variability in initial pouch cell characteristics, including voltage, current, charge capacity, and discharge capacity, across 192 samples from 24 batches. Statistical analysis reveals that voltage remains relatively stable (mean = 3.951V, CV ≈ 6.45%), while charge and discharge capacities exhibit moderate variability (mean = 2.286Ah, CV ≈ 47.99% and mean = 2.350Ah, CV ≈ 52.53%, respectively). Current demonstrates the highest variability, with a mean of 0.280A and a CV of 195.25%, suggesting significant fluctuations possibly due to non-constant current and also likely influenced by process inconsistencies, operational conditions, or measurement sensitivity. Box plot and control chart analyses link many outliers to specific production factors, such as raw material lot changes and equipment maintenance cycles, pinpointing electrode preparation and formation as critical stages for mitigating variability. By integrating statistical insights with practical manufacturing considerations, this work provides a framework for proactive quality control, ultimately supporting scalable and high-quality lithium-ion battery production. While this study focuses on pouch cells, the underlying principles of variability analysis and targeted process improvements remain broadly relevant to other battery formats.

1. Introduction

Lithium-ion batteries (LIBs) have revolutionized energy storage since their commercialization in the 1990s, enabling advancements in portable electronics, electric vehicles (EVs), and grid-scale renewable energy systems [1]. Their high energy density, rechargeability, and declining costs have positioned LIBs as the cornerstone of the global transition to sustainable energy [2]. However, this rapid adoption has exposed critical challenges in manufacturing consistency, particularly as applications demand higher performance, longer lifespans, and stringent safety standards [3]. The automotive industry exemplifies these challenges. Modern EVs require battery packs comprising thousands of individual cells, where even minor inconsistencies in capacity, voltage, or internal resistance can cascade into pack-level imbalances, reducing efficiency, accelerating degradation, and increasing safety risks [4]. For instance, a 5% variation in cell capacity can lead to a 20% reduction in pack lifespan [5]. Such variability underscores the urgent need for precision in LIB manufacturing- a challenge magnified by the industry's shift toward high-volume production to meet global decarbonization targets [6]. Early LIB manufacturing prioritized small-scale production for consumer electronics, where tolerances for variability were relatively lenient [7]. Processes such as slurry coating, calendaring, and electrolyte filling were optimized for flexibility rather than repeatability. However, the rise of EVs and stationary storage has necessitated a paradigm shift. Automotive-grade cells demand near-perfect consistency, with tolerances for capacity and voltage often tightened to <1% [8]. Despite advancements, LIB manufacturing remains a complex, multi-stage process prone to variability.

- Electrode preparation: Heterogeneity in slurry mixing, coating thickness, or drying rates can create localized defects in electrodes [9].
- Cell assembly: Variations in stacking alignment, tab welding, or electrolyte filling introduce mechanical and electrochemical inconsistencies [10].
- Formation and aging: Electrochemical activation steps (e.g., SEI layer formation) are sensitive to temperature and current rates, further amplifying variability [11].

While statistical process control (SPC) and machine learning (ML) have been deployed to monitor these stages [12], most quality control (QC) frameworks focus on post-production screening rather than preemptive variability reduction. For example, clustering cells by capacity post-manufacturing improves pack performance but does not address the root causes of variability [13]. Existing studies predominantly analyze variability in aged or cycled cells [14], overlooking initial characteristics that seed long-term degradation.

Furthermore, few works systematically link variability to specific manufacturing stages or batch-level trends. This gap limits actionable insights for upstream process optimization.
Key Research Questions:

- What is the magnitude of variability in key initial metrics (voltage, capacity) across batches?
- Which manufacturing stages contribute most to this variability?
- How can statistical tools like control charts inform real-time QC interventions?

Objectives:

- Quantify variability in initial pouch cell characteristics using descriptive statistics and coefficient of variation (CV).
- Map outliers to specific manufacturing stages (e.g., electrode coating, formation) through chronological control chart analysis.
- Propose targeted process improvements to reduce variability at critical production junctures.

This study focuses on pouch cells due to their growing dominance in EVs and energy storage, where their high energy density and modularity amplify the consequences of variability [15]. By analyzing 192 samples across 24 batches, we bridge the gap between academic research and industrial practice, offering a roadmap for preemptive QC in high-volume LIB production.

2. Methodology

The dataset comprises 192 pouch cell samples from 24 batches (8 samples/batch), manufactured under standardized protocols, providing a comprehensive overview of initial battery characteristics [16]. To ensure representative analysis:

- Batches were chosen sequentially from a 6-month production period to capture natural process variations (e.g., equipment maintenance cycles, raw material lot changes).
- All 192 samples were included in statistical analyses (e.g., CV, control charts). For visualization (Figures 1-3), one sample per batch (24 total) was randomly selected using Python's numpy.random.choice to avoid cherry-picking biases.
- Outlier Handling: Samples with incomplete data (e.g., interrupted charge cycles) were excluded prior to analysis (3 samples removed).

All initial characterization tests were conducted in a controlled environment. The initial characterization tests for the cells included constant current constant voltage (CCCV) charge - constant current (CC) full discharge (4.2V - 2.7V) at C/2 rate to determine battery discharge capacity. The test procedure is as follows:
Cells were initially charged to 100% SOC using the CCCV profile at C/2 rate.
After reaching 100% SOC, the cells were discharged using constant C/2 current until they reached the lower limits of their assigned SOC ranges (i.e., 20% for 20% - 80% range) for partial cycling.
Constant current charge (always C/2) and constant current discharge (C/2 or 2C) were applied to the cells for cycling between the desired upper and lower limits of SOC (i.e., 20% - 80%).
A rest period of 30 min was applied to allow the cells to relax after every charge and discharge step. The specifications of the battery cells are given in Table 1.

Table 1. Specifications of the pouch cell battery samples

Battery (Parameters)	Specifications (Value)
Capacity Rating	3360 mAh
Cell Chemistry	Cathode: $LiCoO_2$, Anode: graphite
Nominal voltage	3.82 V
Charge cut-off voltage	4.4 V
Discharge cut-off voltage	3.0 V

Each Excel file contains 17 sheets:

- Global Info Sheet: This sheet includes metadata such as Sample No. and Channel, which are essential for identifying and tracking each sample within the file.
- Statistics and Channel Data Sheets: For each of the 8 samples in a file, there are two sheets: one for statistical data and one for channel data. These sheets provide detailed initial performance metrics.

The data includes several key metrics that are critical for assessing initial battery characteristics. Some of the metrics are: Date Time, Test Time (s), Step Time (s), Step Index, Cycle Index, Voltage (V), Current (A), Charge Capacity (Ah), Discharge Capacity (Ah), Charge Energy (Wh), Discharge Energy (Wh), Internal Resistance (Ohm). Figure 1 shows the voltage change during five cycles for one of the sample batteries. The procedure for the batteries is given in Table 2. Figure 2 shows the current change during five cycles.

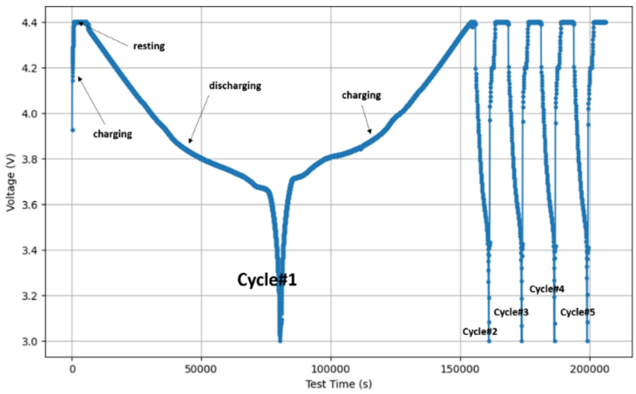

Figure 1. Voltage data for one sample of a pouch Li-ion battery

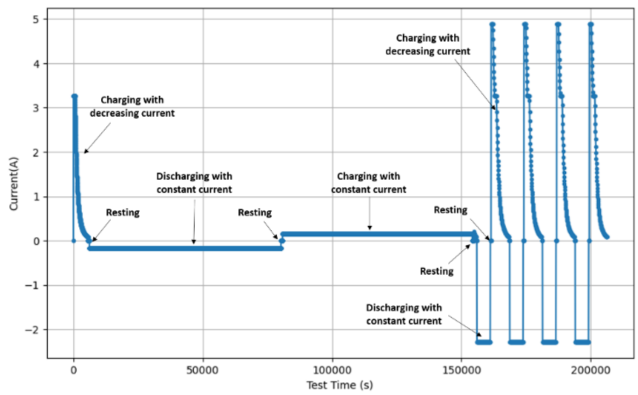

Figure 2. Current data for one sample of pouch Li-ion battery

Table 2. Procedure protocol for the sample batteries

Cycle#	Step numbers														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Charged, 3.93 V	C	R	D	R	C @CC 0.16A	R	R	C	R	D	R	R		
2								C	C	R	D	R	R		
3								C	C	R	D	R	R		
4								C	C	R	D	R	R		
5														C	C

The first cycle in Figure 2 shows a gradual increase in charge capacity, indicating the initial charging phase. The capacity stabilizes (in resting and discharging steps) before increasing sharply, due to an increase in charging. Cycles 2 through 5 display a more consistent pattern, with each cycle showing a similar charge capacity profile. This suggests a stable and repeatable charging process after the initial cycle. After the initial increase, the charge capacity stabilizes in subsequent cycles, indicating that the battery reaches a consistent state of charge. The consistent pattern in later cycles suggests effective control over the charging process, with minimal variability between cycles. Figure 3 presents the charge capacity of the sample battery during the five cycles. Variability in initial battery characteristics was quantified using descriptive statistics (mean, standard deviation), and process stability was evaluated via control charts. The coefficient of variation (CV) normalized variability across metrics (e.g., voltage, capacity). Box plots and control charts (3σ limits) were employed to identify outliers and monitor batch-to-batch consistency. Data processing and visualization were implemented in Python using Pandas (v1.5.3) for dataset aggregation and cleaning, and Matplotlib (v3.7.1) for generating figures.

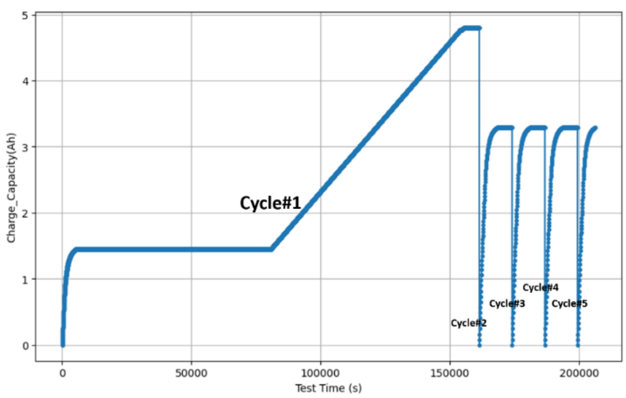

Figure 3. Change in charge capacity over test time across multiple cycles

3. Results and discussion

3.1 Variability analysis

The analysis focused on key metrics such as voltage, current, charge capacity, and discharge capacity.

- The mean voltage across samples was 3.951V, indicating moderate variability.
- The mean current was 0.280A, with a high coefficient of variation (CV=195.25%), suggesting high variability likely due to periods of rest or high-low activity during testing.
- The mean charge capacity was 2.286 Ah, reflecting some variability in the initial state of charge.
- The mean discharge capacity was 2.350 Ah, indicating moderate variability (CV=52.53%), potentially due to outliers or specific test conditions.

Box plots were created for each key metric, voltage, current, charge capacity, and discharge capacity to summarize data distributions and highlight variability (Figure 4). This graphical approach helps identify potential anomalies or inconsistencies in the manufacturing process. The voltage box plot indicates a median around 3.95 V with a relatively narrow interquartile range (IQR), suggesting that most samples exhibit stable voltage levels. The coefficient of variation (CV) is 6.45%, showing minor variability across the dataset. A few outliers appear below the lower whisker, indicating isolated instances of reduced voltage that may warrant further examination. In contrast, the current values exhibit a significantly broader spread, with a mean of 0.280A and a notably high CV of 195.25%.

The large variation suggests considerable fluctuations in current levels, clearly due to non-constant charging and discharging currents and likely due to measurement noise, process inconsistencies, or varying operational conditions. Several samples display extreme current values above the upper whisker, while some approach zero, reflecting the presence of resting or low-current phases. The charge capacity distribution has a median around 2.3 Ah, with an IQR indicating moderate variability across the dataset. The CV of 47.99% suggests substantial batch-to-batch differences, potentially caused by variations in electrode materials, electrolyte composition, or cell formation conditions. Although most values fall within a reasonable range, a few outliers exceed the upper whisker, hinting at isolated cases of higher-than-expected charge retention.

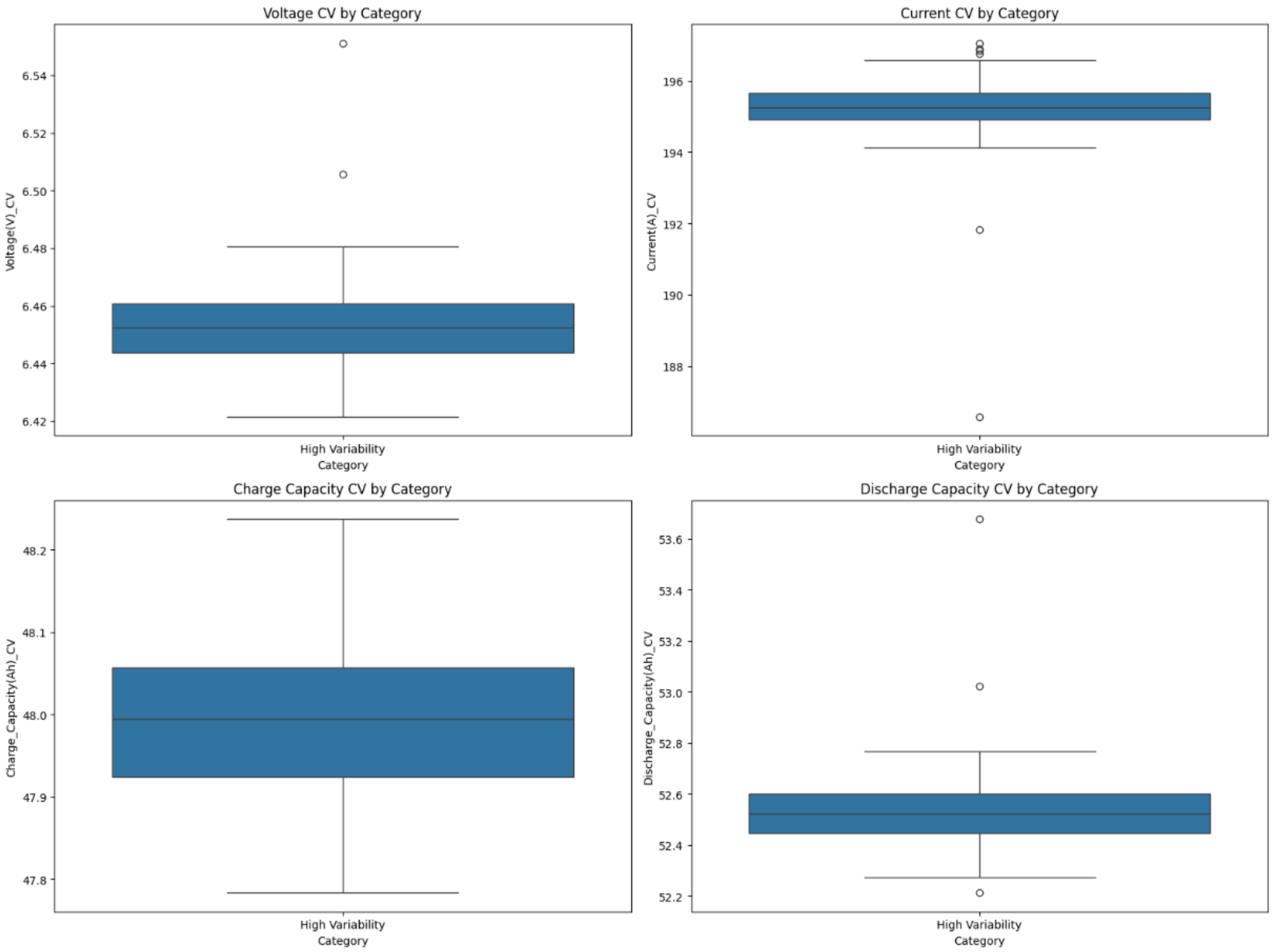

Figure 4. Visualizing the distribution and variability of voltage, current, charge capacity, and discharge capacity across samples

Similarly, the discharge capacity exhibits a median of 2.35 Ah, with whiskers spanning approximately 2.0Ah to 2.7Ah. The CV of 52.53% underscores the substantial variability in discharge performance among samples. The presence of outliers above 2.7Ah indicates that some cells deliver higher-than-typical discharge capacity, which may be attributed to material inconsistencies, manufacturing deviations, or differences in cycling conditions. Among the four key metrics, voltage remains the most stable with a relatively low CV, whereas current demonstrates the highest variability. This analysis provides crucial insights into the variability of each parameter, guiding future quality control efforts. By identifying the root causes of extreme values, such as atypical process conditions, measurement errors, or material inconsistencies, manufacturers can refine production parameters and improve overall cell consistency.

3.2 Control chart analysis

Control charts were utilized to assess the stability of key parameters, voltage, current, charge capacity, and discharge capacity, across different production batches. This analysis aims to detect trends, shifts, and process variations that may not be evident in box plots alone. The control chart for voltage (Figure 5) confirms its relatively stable behavior, with most values remaining within control limits. The mean voltage of 3.951 V and a CV of 6.45% indicate minimal process variation.

No significant outliers or trends suggesting systematic instability were observed. Given that the box plots already show a well-regulated voltage distribution, this control chart reinforces existing findings without introducing new insights. Therefore, it is omitted for brevity.

Unlike voltage, the current exhibits substantial fluctuations, as seen in Figure 6. The mean current is 0.280A, yet it shows a remarkably high CV of 195.25%, indicating significant relative variations. This variability is not entirely because of the non-constant charging protocol, since it correlates with specific batch-level fluctuations that align with equipment maintenance cycles.

In the figures, UCL/LCL are the upper and lower control limits of the values:

$$UCL/LCL = \mu \pm 3\sigma \quad (1)$$

Where μ is the mean and σ is the standard deviation.

Key observations for current:

- Several points exceed upper control limits, suggesting process inconsistencies.
- Irregular fluctuations indicate variability in formation conditions or cycling processes.
- These trends were not fully captured by box plots, making the control chart a valuable addition for diagnosing process variability.

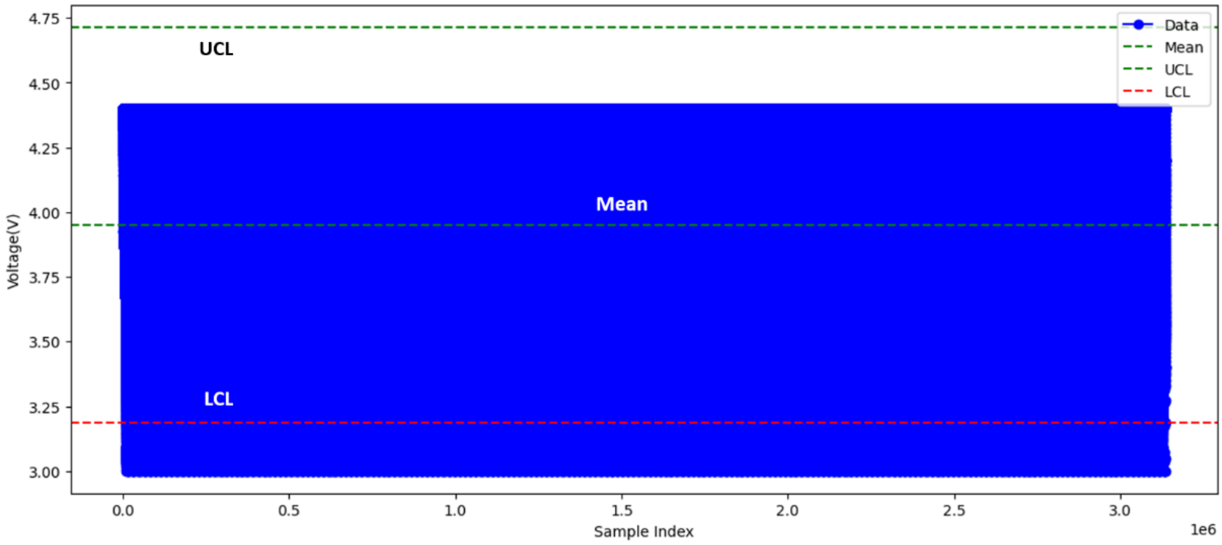

Figure 5. The control chart for voltage for all samples

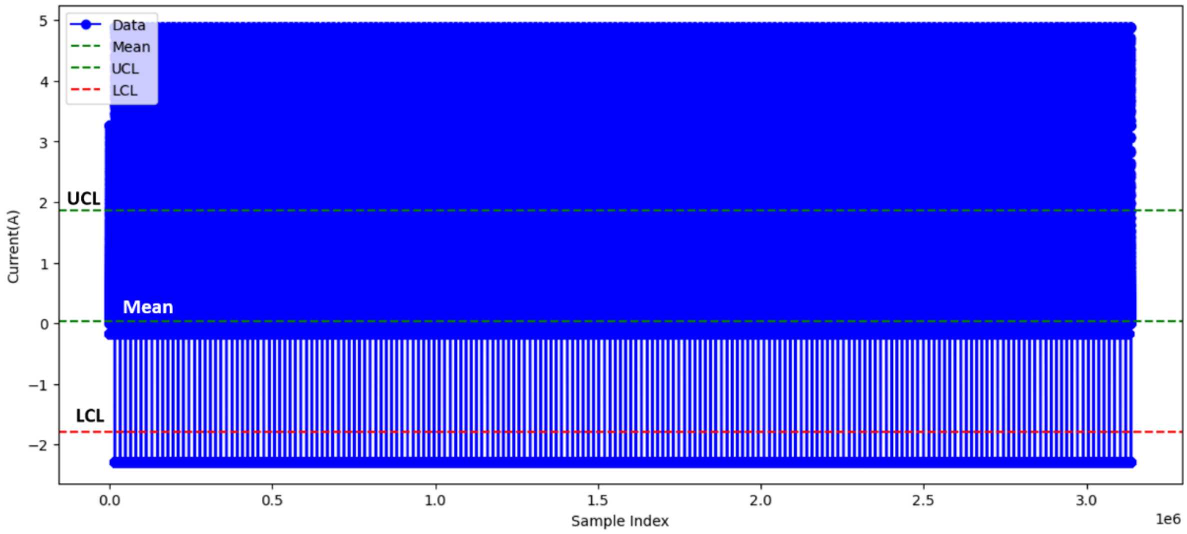

Figure 6. The control chart for current for all samples

Control charts for charge capacity (mean = 2.286 Ah, CV = 47.99%) and discharge capacity (mean = 2.350 Ah, CV = 52.53%) (Figure 7) highlight batch-to-batch variability. Unlike voltage, these parameters show:

- Gradual drifts across multiple batches, potentially linked to electrode material inconsistencies or electrolyte wetting variations.
- Specific points beyond the control limits, aligning with raw material lot changes.
- A pattern of variability that box plots alone do not fully capture, validating the use of control charts in this case.

The box plots in Figure 4, together with the calculated means and coefficients of variation (CV), reveal distinct variability patterns across the four measured parameters:

Voltage (Mean = 3.951, CV = 6.45%): The narrow distribution in the voltage box plot indicates a relatively stable formation process, aligning with industry best practices [16]. A small number of outliers suggests occasional deviations but does not undermine overall voltage consistency.

Current (Mean = 0.280, CV = 195.25%): Although the box plot itself appears not to span a wide range, the small mean current makes even modest fluctuations disproportionately impactful, driving the CV upward. In addition to potential calibration drift and equipment maintenance issues, the intrinsically non-constant current during charge and discharge (e.g., changing between 4.89A and -2.89A) naturally elevates variability measurements. Sporadic spikes or dips observed in maintenance logs [19] likely further amplify these variations.

Charge Capacity (Mean = 2.286, CV = 47.99%): The box plot shows a broad interquartile range and several outliers, signifying significant batch-to-batch variability. Variations in electrode materials (e.g., particle size, binder content) and process parameters (e.g., coating speed, solvent evaporation) are likely contributors.

Discharge Capacity (Mean = 2.350, CV = 52.53%): Discharge capacity exhibits a similar level of variability, with notable outliers in Batches 7, 12, and 19. These outliers coincide with raw material lot changes and calendaring equipment maintenance logs, hinting at material heterogeneity (e.g., anode thickness variations) or process inconsistencies (e.g., electrolyte wetting) [17, 18].

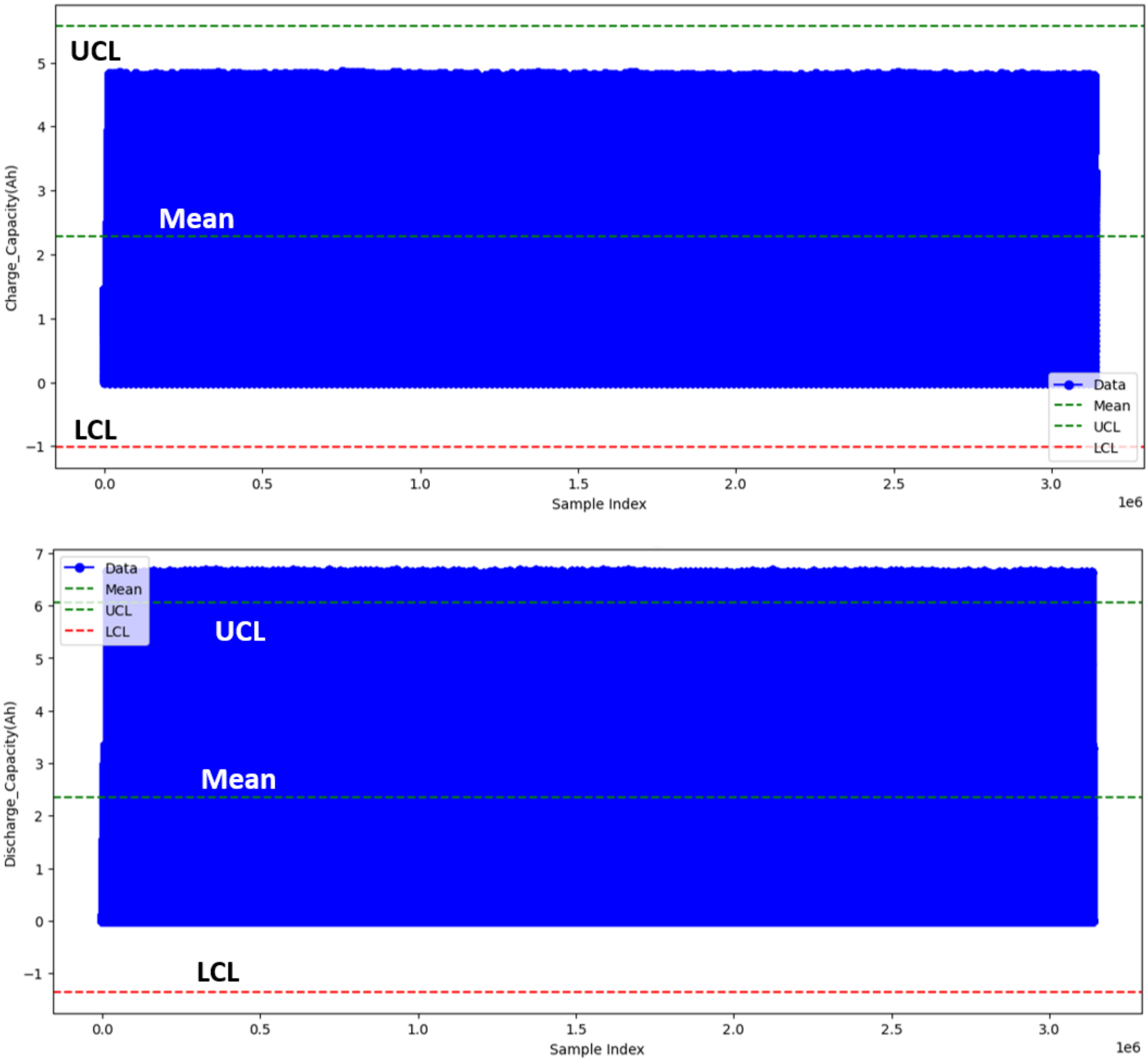

Figure 7. The control chart for charge and discharge capacities for all samples

3.3 Root causes and contributing factors

3.3.1 Material heterogeneity

- Discharge capacity outliers correlate with specific raw material lot changes, suggesting feedstock variability (e.g., graphite particle size or binder composition).
- Even minor deviations in electrode thickness (±3 µm) or slurry viscosity can substantially impact final capacity [20, 21].

3.3.2 Equipment calibration and process drift

- The very high CV for current is partly explained by the small mean current value. Minor measurement errors or calibration drifts become disproportionately large in relative terms.
- Maintenance records indicate that post-maintenance recalibration may not have been fully stabilized before production resumed, causing sporadic shifts in current measurements.

3.3.3 Non-constant charge/discharge profiles

- Battery formation and cycling often employ varying current profiles, which can elevate variability when viewed as a single metric.
- This inherent fluctuation compounds any calibration or measurement inconsistencies, driving the CV higher than in processes where current is held more constant.

3.3.4 Electrolyte wetting and formation procedures

- Subtle variations in electrolyte wetting can lead to uneven solid-electrolyte-interphase (SEI) formation, impacting both charge and discharge capacities.
- Voltage is relatively stable, but capacity and current measurements are more sensitive to small deviations in wetting, temperature, and humidity.

3.4 Strategic recommendations for mitigating variability

3.4.1 Material standardization

- Stricter specifications: Tighten control over critical material attributes (e.g., binder ratio, particle size distribution) to minimize the likelihood of outlier batches.
- Advanced coating techniques: Investigate dry electrode processing or enhanced slurry mixing protocols to reduce thickness variability [22].

3.4.2 Enhanced process control

- Real-Time sensing: Implement inline sensors (e.g., ultrasonic thickness gauges [23]) on calendaring and coating lines to catch off-spec thickness or density in real time.
- Predictive maintenance: Employ AI-based models to anticipate calibration drift in formation equipment, allowing for proactive rather than reactive interventions.

3.4.3 Quality control (QC) integration

- In-Line SPC: Shift from post-production clustering to in-line statistical process control (SPC) during electrode preparation [24]. Immediate feedback helps prevent entire batches from drifting.
- Variability fingerprinting: Establish batch-specific profiles linking key process parameters (e.g., slurry viscosity, ambient conditions) to final capacity, facilitating targeted root-cause analyses.

3.5 Broader implications and future directions

3.5.1 Cost and reliability gains

- Reducing early-stage variability can cut production costs by up to 15% for EV battery packs, largely by decreasing rework, scrap, and warranty claims [25].

- In grid-scale storage, higher consistency aids in accurate state-of-health (SoH) monitoring, extending system longevity [26].

3.5.2 Further investigations

- Cell geometry comparisons: Contrast pouch, prismatic, and cylindrical cells to identify geometry-specific sensitivities to process deviations.
- Environmental control: Examine humidity and temperature effects during electrolyte filling, factors often overlooked in standard QC protocols [27].
- Second-life applications: Investigate how initial variability affects the viability of second-life battery usage, where performance uniformity is paramount [28].

Both the box plot data and the high CV values underscore the interplay of material heterogeneity, equipment calibration, and the intrinsically variable current profiles used in battery charging/discharging. By refining material specifications, improving process controls, and better accommodating non-constant current regimes, manufacturers can substantially reduce outliers and enhance overall process consistency.

3.6 Limitations

This study’s focus on pouch cells limits generalizability to prismatic/cylindrical designs. Additionally, the dataset excludes seasonal variations (e.g., summer vs. winter production), which may influence electrolyte viscosity [29]. By dissecting initial variability in pouch cell manufacturing, this work provides a blueprint for preemptive quality control. The integration of material standardization, real-time monitoring, and AI-driven analytics represents a paradigm shift from reactive screening to proactive consistency management- a critical step toward scalable, sustainable LIB production.

4. Conclusion

The comprehensive analysis of battery manufacturing revealed consistent voltage levels across batches, demonstrating effective control over this critical parameter. The stability in voltage serves as a strong indicator of a well-managed manufacturing process, highlighting the manufacturer's ability to maintain precise electrical characteristics. However, the study also uncovered higher variability in current, charge, and discharge capacity, with notable outliers identified. These variations signal potential areas where the manufacturing process could benefit from further refinement to ensure more uniform performance across battery cells. Such variability can significantly impact battery reliability and overall performance, underscoring the critical need for robust quality control measures. The observed variations in key metrics emphasize the importance of maintaining consistent manufacturing processes. Addressing these inconsistencies is crucial for optimizing battery life, performance, and reliability. Continuous monitoring and targeted interventions will be essential in mitigating these variations and enhancing overall manufacturing consistency. Looking forward, several promising research directions emerge from these findings. Researchers should prioritize conducting in-depth analyses to explore the root causes of variability, focusing on intricate interactions between material properties, equipment calibration, and environmental factors. This comprehensive approach can provide deeper insights into the sources of performance inconsistencies. Advanced monitoring and analytics tools represent another critical avenue for future investigation. Developing real-time monitoring capabilities could enable proactive quality control, allowing manufacturers to identify and address potential issues before they impact final product quality. Such technological innovations could revolutionize the approach to battery manufacturing quality assurance. Material science and manufacturing process innovations also present significant opportunities for improvement. Exploring novel materials and advanced manufacturing techniques could potentially reduce variability and enhance overall battery performance and reliability. This approach requires interdisciplinary collaboration between materials scientists, engineers, and manufacturing experts. Longitudinal studies will be instrumental in understanding the long-term stability of the manufacturing process. By tracking changes in variability and performance over extended periods, researchers can gain comprehensive insights into the manufacturing process's evolution and identify potential improvement strategies. These research directions collectively represent a comprehensive approach to addressing manufacturing variability. By systematically investigating and addressing the sources of inconsistency, researchers and manufacturers can work towards developing more reliable, high-performance battery technologies. The ultimate goal is to create manufacturing processes that consistently produce high-quality battery cells with minimal variability, meeting the increasingly demanding requirements of modern technological applications. The path forward involves a commitment to continuous improvement, innovative research, and a holistic approach to understanding and controlling the complex factors that influence battery manufacturing quality.

Ethical issue

The author is aware of and complies with best practices in publication ethics, specifically concerning authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere in any language.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the corresponding author.

Conflict of interest

The author declares no potential conflict of interest.

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