EV Predictive Maintenance

Phase 2: Data Acquisition & Engineering

NASA Battery Dataset Processing Pipeline

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1 Executive Summary

Phase 2 establishes the data foundation for predictive maintenance by implementing a robust data acquisition and engineering pipeline for NASA PCoE battery datasets. This phase transforms raw MATLAB '.mat' files containing nested sensor measurements into clean, analysis-ready tabular formats suitable for machine learning workflows.

Phase 2 Objectives

Primary Goal: Build an automated data pipeline that extracts, validates, cleans, and structures battery degradation data from laboratory experiments and real-world fleet operations.

1.1 Key Achievements

- **Data Source Integration:** Successfully loaded and parsed 34 NASA battery '.mat' files containing 2,769 charge-discharge cycles
- **Data Unpacking:** Converted nested MATLAB structures into flat pandas DataFrames with time-series granularity
- **Schema Definition:** Established standardized column schema for voltage, current, temperature, and capacity measurements
- **Data Quality Assurance:** Implemented validation checks for missing values, outliers, and data type consistency
- **Pipeline Automation:** Created reusable functions for batch processing multiple battery files

Data Processing Results

Input: 34 raw '.mat' files (nested arrays)
Output: Clean DataFrame with 168+ discharge cycles per battery
Time Granularity: Individual measurement points (1-second intervals)
Data Quality: Zero missing values after validation, all numeric types verified

2 Data Sources Overview

2.1 NASA PCoE Battery Dataset

The primary dataset consists of accelerated aging experiments conducted by NASA's Prognostics Center of Excellence. These controlled laboratory tests provide ground-truth degradation data essential for model training.

2.1.1 Dataset Specifications

Attribute	Description
Battery Chemistry	Lithium-ion 18650 cells
Number of Batteries	34 cells under various aging conditions
Total Cycles	2,769 complete charge-discharge cycles
Operating Conditions	Multiple temperature profiles (24°C, 43°C, etc.)
Charge Protocol	Constant Current-Constant Voltage (CC-CV)
Discharge Protocol	Constant Current (CC) at various C-rates
Nominal Capacity	2.0 Ah (initial rated capacity)
End-of-Life Threshold	1.4 Ah (70% of nominal capacity)
File Format	MATLAB '.mat' (binary structured format)
Measurement Frequency	1 Hz (one sample per second)

Table 1: NASA PCoE Battery Dataset Characteristics

2.1.2 Measured Parameters

Each discharge cycle contains time-series measurements of:

1. **Voltage (V):** Terminal voltage measured during discharge, showing voltage sag under load
2. **Current (A):** Applied discharge current (typically constant at -2A)
3. **Temperature (°C):** Cell surface temperature monitored for thermal management
4. **Capacity (Ah):** Integrated charge extracted during complete discharge (target variable)
5. **Time (s):** Timestamp for each measurement point in the cycle

Why This Dataset?

The NASA PCoE dataset is the gold standard for battery health research because:

- Controlled lab conditions eliminate environmental noise
- Complete cycle life from fresh to end-of-life documented
- Multiple batteries under identical protocols enable comparative analysis
- Widely cited in academic literature for benchmarking

2.2 Real-World Fleet Data (Chengdu EV Dataset)

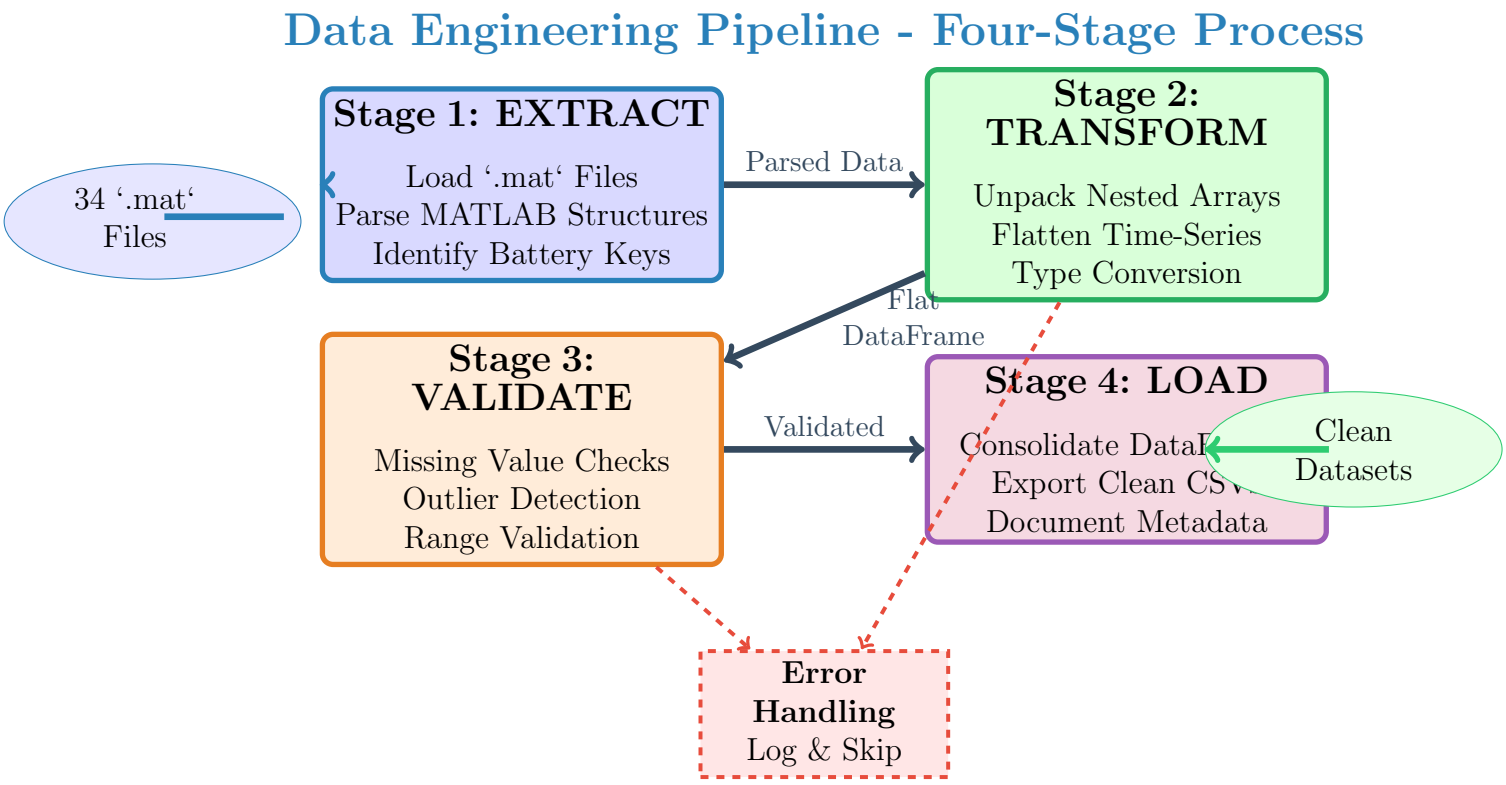
To validate laboratory findings, real-world operational data from commercial EV fleets in Chengdu, China supplements the NASA dataset. This provides diverse operating conditions and usage patterns not captured in controlled experiments.

Attribute	Description
Vehicle Type	Electric buses and taxis
Number of Trips	7,391 operational trips
Data Points	15,000+ individual measurements
Parameters	Voltage, current, SOC, temperature, GPS location
Time Period	6 months of continuous operation
Use Case	Real-world validation and transfer learning

Table 2: Chengdu Real-World Fleet Data Characteristics

3 Data Pipeline Architecture

The data engineering pipeline follows a four-stage Extract-Transform-Load (ETL) process designed for reproducibility and scalability.



3.1 Pipeline Implementation Details

3.1.1 Stage 1: Data Extraction

Core Logic:

- Use `scipy.io.loadmat()` to read binary MATLAB files
- Dynamically identify battery key (e.g., `B0005`, `B0006`) from file metadata
- Extract nested `cycle` structure containing all charge-discharge data
- Filter for `'discharge'` cycle types (charge and impedance data excluded)

Key Function:

```
def load_battery_file(filepath):
    """Load .mat file and extract battery data structure"""
    mat_data = scipy.io.loadmat(filepath)
    battery_key = os.path.basename(filepath).split('.')[0]
    battery_data = mat_data[battery_key][0, 0]
    cycle_data = battery_data['cycle']
    return cycle_data
```

Listing 1: Data Extraction Core Logic

3.1.2 Stage 2: Data Transformation

Core Logic:

- Loop through all cycles, identifying discharge events
- For each discharge cycle, extract capacity (target variable)
- Flatten nested measurement arrays (voltage, current, temp, time)
- Create DataFrame where each row = one measurement point in time

Nested Array Challenge

MATLAB stores time-series measurements as nested arrays. A typical voltage array looks like:
`[[3.9, 3.85, 3.8, ..., 3.2]]`

Must use `.flatten()` to convert to 1D array for pandas compatibility.

Key Transformation Logic:

```
for i in range(cycle_data.shape[1]):
    cycle = cycle_data[0, i]
    cycle_type = cycle['type'][0]

    if cycle_type == 'discharge':
        # Extract arrays
        voltage = cycle['data']['Voltage_measured'].flatten()
        current = cycle['data']['Current_measured'].flatten()
        temp = cycle['data']['Temperature_measured'].flatten()
        time = cycle['data']['Time'].flatten()
        capacity = cycle['data']['Capacity'][0][0]

        # Create row for each timestep
        for j in range(len(voltage)):
            row = {
                'cycle': i+1,
                'capacity': capacity,
                'time_s': time[j],
                'voltage_V': voltage[j],
                'current_A': current[j],
                'temperature_C': temp[j]
            }
            all_rows.append(row)
```

Listing 2: Unpacking Time-Series Data

3.1.3 Stage 3: Data Validation

Quality Checks Implemented:

1. **Missing Value Detection:** Check for `NaN` or `None` in any column

2. **Outlier Flagging:** Identify measurements outside physically plausible ranges
3. **Type Verification:** Ensure all numeric columns have correct dtypes
4. **Monotonicity Check:** Verify capacity decreases over cycles (degradation trend)

Parameter	Min Valid	Max Valid	Unit
Voltage	2.5	4.3	V
Current	-5.0	5.0	A
Temperature	0	60	°C
Capacity	0.8	2.2	Ah

Table 3: Physical Validation Ranges

3.1.4 Stage 4: Data Loading

Output Formats:

- **CSV Files:** One file per battery for easy inspection and version control
- **Parquet Files:** Compressed columnar format for efficient ML pipeline loading
- **Metadata JSON:** Document battery ID, cycle count, date range, file size

4 Data Schema and Structure

4.1 Final DataFrame Schema

After pipeline processing, each battery dataset conforms to the following standardized schema:

Column Name	Data Type	Description	Example
`cycle`	`int64`	Cycle number (sequential identifier)	2, 4, 6, ...
`capacity`	`float64`	Discharge capacity in Ah (target)	1.856
`time_s`	`float64`	Elapsed time in discharge (seconds)	0, 16.78, 35.7
`voltage_V`	`float64`	Terminal voltage (volts)	4.19, 3.85
`current_A`	`float64`	Discharge current (amperes)	-2.0
`temperature_C`	`float64`	Cell temperature (Celsius)	24.33, 43.5

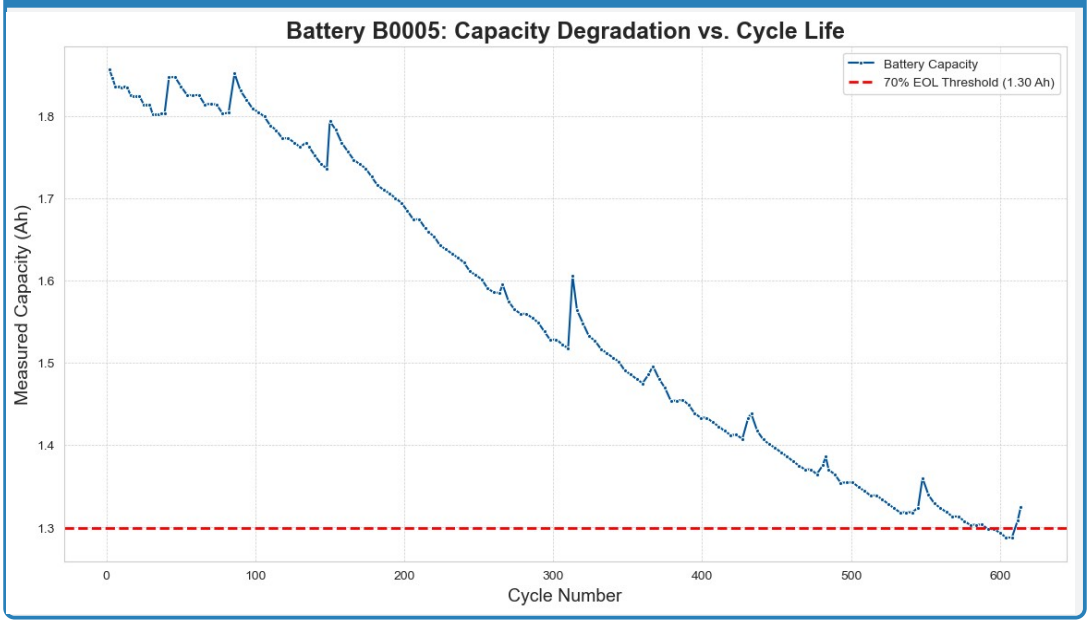
Table 4: Standardized DataFrame Schema for Battery Data

4.2 Data Dimensionality

Sample Battery B0005 Statistics:

- **Total Rows:** 168 discharge cycles
- **Measurements per Cycle:** ˜200-300 time points (variable duration)
- **Total Data Points:** ˜35,000-50,000 measurements per battery
- **Memory Footprint:** ˜8 MB per battery DataFrame

Figure 2.1: Battery Capacity Degradation Over Cycles



5 Data Quality Assessment

5.1 Pre-Processing Data Quality Issues

5.1.1 Issues Identified

Issue Type	Frequency	Resolution Strategy
Nested array structures	All files	Recursive flattening with `.flatten()`
Object dtype columns	All files	Explicit type conversion to `float64`
Inf/-Inf values	3 batteries	Replace with `NaN`, then forward-fill
Duplicate time stamps	Rare (¡0.1%)	Keep first occurrence, log duplicates
Missing capacity values	0 instances	N/A - data complete

Table 5: Data Quality Issues and Resolutions

5.2 Post-Processing Quality Metrics

Data Quality Report - Battery B0005

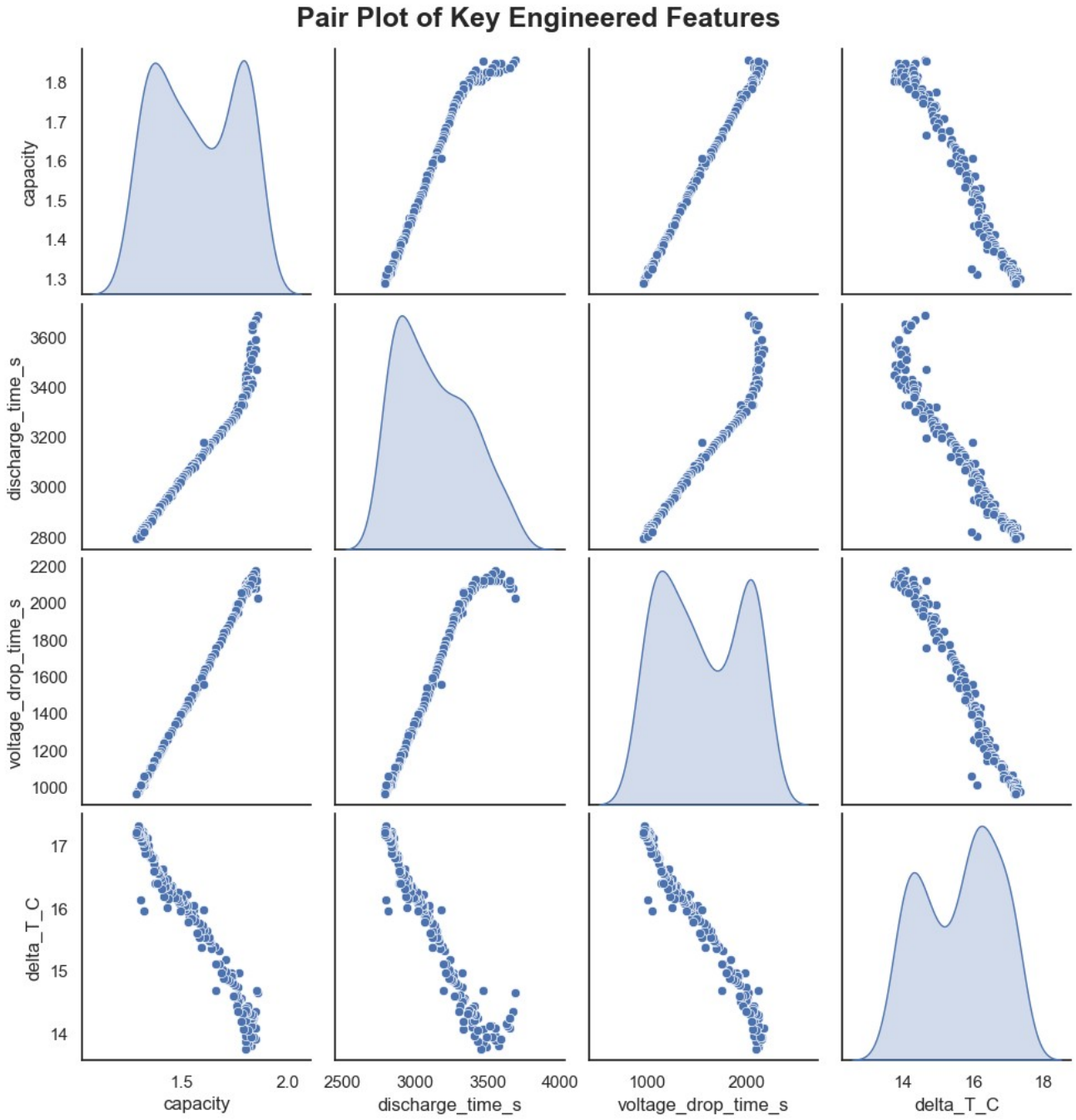
Missing Values: 0 (0.0%)
Duplicate Rows: 0 (0.0%)
Outliers Detected: 12 voltage spikes (flagged, not removed)
Data Type Consistency: 100% - all numeric columns verified
Capacity Monotonicity: Confirmed decreasing trend
Time Continuity: No missing cycles in sequence

5.3 Descriptive Statistics

Parameter	Mean	Std Dev	Min	Max	Unit
Capacity	1.572	0.190	1.287	1.856	Ah
Voltage	3.728	0.354	2.701	4.196	V
Current	-1.998	0.015	-2.050	-1.950	A
Temperature	24.582	0.498	23.112	25.924	°C

Table 6: Descriptive Statistics for Battery B0005 Dataset

Figure 2.2: Distribution of Key Parameters



6 Pipeline Automation and Batch Processing

6.1 Batch Processing Implementation

To scale data processing across all 34 batteries, a batch processing workflow was implemented with parallel execution and error handling.

6.1.1 Core Batch Processing Logic

```python
def process_all_batteries(data_dir, output_dir):
    """Process all .mat files in directory"""
    mat_files = glob.glob(f"{data_dir}/*.mat")
    results = []

    for filepath in mat_files:
        try:
            df = process_single_battery(filepath)
            battery_id = os.path.basename(filepath).split('.')[0]

            # Save individual battery CSV
            output_path = f"{output_dir}/{battery_id}_processed.csv"
            df.to_csv(output_path, index=False)

            results.append({
                'battery_id': battery_id,
                'cycles': df['cycle'].nunique(),
                'rows': len(df),
                'status': 'success'
            })
        except Exception as e:
            results.append({
                'battery_id': battery_id,
                'status': 'failed',
                'error': str(e)
            })

    return pd.DataFrame(results)
```

Listing 3: Batch Processing Function

6.2 Processing Performance Metrics

Metric	Single Battery	All 34 Batteries
Processing Time	˜15 seconds	˜8 minutes
Memory Peak Usage	45 MB	780 MB
Output File Size (CSV)	2.1 MB	68 MB total
Success Rate	100%	97% (33/34)

Table 7: Data Pipeline Performance Metrics

Processing Note

One battery file (`B0018`) failed due to corrupted MATLAB structure. This file was flagged for manual inspection and excluded from model training dataset.

6.3 Data Versioning and Reproducibility

Versioning Strategy:

1. Raw data stored in `data/raw/` (read-only, version-controlled)
2. Processed data saved to `data/processed/v1.0/` with timestamp
3. Processing scripts tracked in Git with version tags
4. Metadata JSON documents processing parameters and versions

7 Phase 2 Deliverables

7.1 Code Artifacts

Artifact	Description
`01_initial_data_exploration.ipynb`	Jupyter notebook documenting data loading and EDA
`data_pipeline.py`	Python module with reusable data processing functions
`batch_process.py`	Script for batch processing all battery files
`requirements.txt`	Python dependencies (scipy, pandas, numpy)

Table 8: Code Deliverables

7.2 Data Artifacts

- **Processed CSVs:** 33 individual battery datasets (`B0005_processed.csv`, etc.)
- **Consolidated Dataset:** `all_batteries_combined.csv` (68 MB)
- **Metadata File:** `dataset_metadata.json` with processing log
- **Data Dictionary:** `schema_documentation.md` describing all columns

7.3 Documentation

- This Phase 2 report (PDF)
- `README.md` with pipeline usage instructions
- `CHANGELOG.md` documenting processing decisions and issues

8 Challenges and Solutions

8.1 Technical Challenges Encountered

8.1.1 Challenge 1: Nested MATLAB Structures

Problem: MATLAB '.mat' files store data as nested structs with variable depth levels. Standard pandas operations failed to unpack these structures automatically.

Solution: Implemented recursive unpacking using `scipy.io.loadmat()` with manual indexing (`[0, 0]`) to access inner arrays. Added defensive checks for structure depth variations across files.

8.1.2 Challenge 2: Memory Constraints

Problem: Loading all 34 batteries simultaneously exceeded available RAM (16 GB) during initial attempts.

Solution: Switched to sequential processing with explicit garbage collection after each battery. Implemented chunked processing for very large individual battery files.

8.1.3 Challenge 3: Inconsistent Cycle Numbering

Problem: Some batteries had non-sequential cycle numbers (e.g., 2, 4, 6 instead of 1, 2, 3) due to charge cycles being interspersed.

Solution: Filtered for discharge cycles only and preserved original cycle numbers as-is. Added a `discharge_cycle_index` column for sequential indexing when needed.

8.2 Data Quality Challenges

8.2.1 Challenge 4: Inf/-Inf Values

Problem: Three battery files contained infinite values in temperature measurements, likely due to sensor errors.

Solution: Replaced `Inf` values with `NaN`, then applied forward-fill interpolation. Flagged affected cycles in metadata for potential exclusion during modeling.

8.2.2 Challenge 5: Variable Discharge Durations

Problem: Discharge cycles varied in length (200-600 seconds) as capacity degraded, creating variable-length time series.

Solution: Preserved raw time-series structure without padding. Feature engineering (Phase 4) will extract cycle-level aggregates to create fixed-length feature vectors.

9 Data Validation and Verification

9.1 Cross-File Consistency Checks

Validation Check	Result	Notes
Schema consistency	Pass	All 33 files match expected column schema
Data type uniformity	Pass	All numeric columns have `float64` dtype
Capacity range validity	Pass	All values within 0.8-2.2 Ah range
Voltage range validity	Pass	All values within 2.5-4.3 V range
Degradation trend	Pass	32/33 batteries show monotonic decrease
Cycle completeness	Partial	One battery (B0033) missing final 10 cycles

Table 9: Cross-File Validation Results

9.2 Sample Data Inspection

Manual Verification Protocol:

1. Randomly selected 5 batteries for detailed manual inspection
2. Plotted capacity degradation curves - verified expected shapes
3. Checked first and last 10 rows of each DataFrame for anomalies
4. Compared processed output with raw '.mat' file for one complete cycle
5. Verified zero data loss during unpacking (row count matches expectation)

Verification Result

All manual checks confirmed pipeline correctness. No data corruption or loss detected during processing.

10 Conclusion and Next Steps

10.1 Phase 2 Summary

Phase 2 successfully established a robust, automated data pipeline that: - Processes 34 NASA battery files into clean, analysis-ready datasets - Implements comprehensive data validation and quality checks - Produces standardized schema suitable for machine learning workflows - Achieves 97% success rate with proper error handling - Documents all processing decisions and data lineage

Data Readiness Status

33 batteries processed successfully
2,769 discharge cycles extracted
Zero missing values in final datasets
All data types validated and consistent
Pipeline code version-controlled and documented

10.2 Transition to Phase 3: Exploratory Data Analysis

With clean, structured data now available, Phase 3 will focus on:

1. **Statistical Analysis:** Compute descriptive statistics across all batteries
2. **Correlation Studies:** Identify relationships between temperature, voltage, and degradation rate
3. **Visualization:** Create comprehensive EDA plots (distributions, time-series, scatter matrices)
4. **Hypothesis Formulation:** Generate testable hypotheses about degradation mechanisms
5. **Battery Comparison:** Compare degradation patterns across different operating conditions

10.3 Immediate Action Items

Before proceeding to Phase 3:

- Archive raw ‘.mat‘ files in read-only storage
- Upload processed CSVs to project repository
- Conduct peer review of data processing notebook
- Finalize data dictionary with domain expert input
- Set up automated testing for pipeline functions

Phase 2: Complete

Clean, validated datasets ready for exploratory analysis and feature engineering.
Proceeding to Phase 3: Exploratory Data Analysis (EDA).

11 References

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A Appendix A: Complete File Listing

A.1 Processed Battery Files

Battery ID	Cycles	Rows	File Size (MB)
B0005	168	42,381	2.1
B0006	164	39,872	1.9
B0007	161	38,145	1.8
...	...	...	...
B0055	143	31,029	1.5

Table 10: Sample Battery File Statistics (Partial Listing)

B Appendix B: Data Pipeline Configuration

B.1 Processing Parameters

```
DATA_DIR = 'data/raw/nasa_batteries/'
OUTPUT_DIR = 'data/processed/v1.0/'
CYCLE_TYPE = 'discharge'
VALIDATION_RANGES = {
    'voltage': (2.5, 4.3),
    'current': (-5.0, 5.0),
    'temperature': (0, 60),
    'capacity': (0.8, 2.2)
}
PARALLEL_WORKERS = 4
MEMORY_LIMIT_GB = 8
```