*Temporary Title:* *Characterizing Real-World EV Battery Usage: A Statistical Foundation for Synthetic Data Generation*

**Temporary Abstract**

This paper presents a statistical analysis of real-world electric vehicle (EV) battery usage patterns based on a dataset of 70 driving sessions collected under various conditions. The study includes downsampling, header correction, and metadata generation across both idle and active driving scenarios. Key visualizations — including energy distribution histograms, pie charts of trip types, and radar plots comparing key metrics — provide insight into current, voltage, temperature, and SoC dynamics. These findings establish a realistic foundation for the generation of long-term synthetic datasets that will power future simulation-based studies of battery behavior and state-of-charge estimation models.

**1. Introduction**

As the deployment of electric vehicles (EVs) continues to grow, the need for accurate, long-term simulation of battery behavior has become critical — both for state-of-charge (SoC) estimation and for performance optimization under varying real-world conditions [ref1][ref2]. Many advanced machine learning approaches, including LSTM and hybrid neural models, rely heavily on synthetic data for training and evaluation [ref3][ref4]. However, synthetic datasets that are not rooted in statistically representative real-world patterns risk leading to models that overfit artificial trends while failing to generalize under true operating scenarios [ref5][ref6]. One key challenge lies in the lack of real driving dynamics — short trips, mixed driving-idling sequences, and opportunity charging — all of which are common in real EV usage but often underrepresented in lab or simulation environments [ref7][ref8]. Real-world datasets provide a solution, but they bring their own challenges: non-uniform sampling rates, inconsistent headers, and missing or noisy entries [ref9][ref10].

To address these gaps, we introduce a multi-phase EV Battery SoC Simulator. This project aims to bridge the gap between synthetic generation and physical driving patterns by analyzing, modeling, and extending actual EV trip data. In this paper, we present Phase 0, which focuses on the statistical characterization of real-world EV battery usage. Our dataset includes 70 driving sessions, labeled TripA01 to TripA32 and TripB01 to TripB38, covering a diverse set of vehicle states, including driving, idling, and partial charging. Each trip is treated as a high-resolution time series and is cleaned and standardized to a 1-second sampling frequency. Unlike many studies that exclude “uninteresting” data such as short idle periods or low-energy sessions, we intentionally preserve all driving sessions, recognizing that such fragments often capture thermal stabilization, light-duty patterns, and regenerative behavior [ref11][ref12][ref13]. This inclusive approach allows us to build a metadata-rich characterization that supports realistic synthetic modeling in later phases. Our analysis includes temporal downsampling, column repair, dimensional alignment, and statistical visualization (e.g., SoC histograms, trip type pie charts, radar comparisons). These outputs serve as the ground truth foundation for synthetic SoC generation and future studies using both rule-based and AI-based simulation methods [ref14][ref15][ref16].

Moreover, this paper complements ongoing efforts in synthetic data generation and battery health modeling, where high-fidelity labeled datasets are increasingly important for AI-driven EV systems [ref17][ref18]. We argue that a well-characterized real dataset is not only a prerequisite for reliable simulation, but also a stepping stone for digital twin frameworks and second-life battery deployment studies [ref19][ref20]. The remainder of this article is organized as follows: Section 2 details the dataset and its structure; Section 3 describes our preprocessing and cleaning pipeline with mathematical explanations; Section 4 provides statistical insights through visualizations; Section 5 presents metadata generation results and interpretation; and Section 6 concludes with implications for synthetic modeling and future work.

**2. Dataset Description**

This section presents the structure and characteristics of the real-world EV dataset used in Phase 0. We explore its origin, organization, recorded signals, and the specific challenges it posed during preprocessing. Understanding the underlying dataset is essential before any statistical or synthetic modeling effort can be meaningfully conducted — especially given the diversity and irregularity of real driving behaviors.

**2.1 Dataset Origin and Scope**

The dataset used in this study originates from an open-access repository published on IEEE DataPort, where it was collected under real driving conditions in Germany using a fully electric vehicle [ref21]. It includes high-resolution logs of various electrical and thermal parameters, representing a wide spectrum of vehicle behavior such as regular commuting, city navigation, idling, partial charging, and cabin heating events. For the purposes of this project, we selected 70 representative trip files and divided them into two labeled groups: TripA01 to TripA32 and TripB01 to TripB38. Each file captures a complete and continuous driving session, saved in .csv format, with temporal sequences ranging from under two minutes to over forty minutes in duration. This structure aligns with modern practices in EV behavioral analysis, where isolated driving bursts are treated as atomic units for SoC tracking and energy profiling [ref22][ref23].

The sessions cover diverse driving scenarios — including low-speed urban traffic, regenerative braking events, and moments of extended idling — all of which are relevant to characterizing SoC dynamics realistically. Unlike curated or benchmarked datasets that often remove or aggregate less “useful” segments, this dataset retains them all. Such a decision ensures that subsequent synthetic generation efforts are grounded in realistic battery behavior, especially for transitions like stop-and-go movement, thermal equilibrium phases, or charge acceptance following aggressive braking [ref24][ref25]. What makes this dataset particularly valuable is its raw and minimally processed form. This provides both opportunities and challenges: on one hand, it mirrors the messy nature of onboard vehicle logs; on the other, it allows us to build a transparent, step-by-step pipeline for data cleaning, alignment, and modeling — which is precisely what this Phase 0 analysis sets out to do.

2.2 Signal Inventory and Units

Each CSV file in the dataset contains time-series measurements captured from the vehicle’s battery system, environmental sensors, and drivetrain components. However, the set of recorded signals is not identical across all files — some trips contain only a core set of electrical parameters, while others include additional thermal and dynamic data. This variability is typical of real-world EV datasets and reflects how logging configurations can vary between sessions or firmware versions [ref26]. To maintain consistency and prepare for statistical comparison, we defined two categories of signals: core signals, which are present in nearly every trip and are used in all major Phase 0 analyses; and auxiliary signals, which are used for extended characterizations such as radar plots and thermal mapping but may be missing in some files. The core signals include the battery voltage, current, internal temperature, displayed state-of-charge (SoC), and a time index. These form the backbone of SoC estimation and synthetic sequence modeling and are retained throughout all processing stages. These signals are particularly sensitive to dynamic behaviors like acceleration, regenerative braking, and heating events — and thus provide a reliable lens into battery usage patterns [ref27][ref28].

The auxiliary signals offer added insight into driver actions and thermal conditions. For instance, Motor Torque [Nm] correlates with instantaneous power demand, while cabin and vent temperatures inform us about energy diverted to HVAC systems — a known source of parasitic load in EVs, especially during winter driving [ref29][ref30]. Table 1 summarizes the key signals identified across the dataset, including their physical meaning and unit of measurement.

Table 1. Description of commonly used signals in Phase 0 dataset.

|  |  |  |  |
| --- | --- | --- | --- |
| **Signal Name** | **Description** | **Unit** | **Category** |
| Time [s] | Elapsed time since the start of the trip | Seconds | Core |
| Battery Voltage [V] | Voltage across the battery pack | Volts (V) | Core |
| Battery Current [A] | Current drawn from or supplied to the battery | Amperes (A) | Core |
| Battery Temperature [°C] | Internal battery pack temperature | °Celsius | Core |
| Displayed SoC [%] | State-of-Charge displayed to the driver (reference only) | Percent (%) | Core |
| Cabin Temperature Sensor [°C] | Temperature inside the cabin (useful for heating analysis) | °Celsius | Auxiliary |
| Temperature Vent Right [°C] | Air vent temperature near passenger side | °Celsius | Auxiliary |
| Motor Torque [Nm] | Instantaneous torque from the electric motor | Newton-meters | Auxiliary |
| Vehicle Speed [km/h] | Ground speed of the vehicle | km/h | Auxiliary |

While our focus in this article is primarily on the core electrical signals, we retain all auxiliary columns in the cleaned files to preserve analysis flexibility in future phases. These extended features may later serve as useful predictors for thermal modeling, HVAC energy estimation, or advanced driver profiling. It’s worth noting that some files contained signals with minor header corruption or unusual formatting — for example, missing closing brackets or duplicate column names. These were addressed during the cleaning phase (Section 3), but are mentioned here to underline the non-trivial nature of working with real-world log data. Unlike idealized benchmark datasets, these logs exhibit the exact kind of messiness that one would expect from in-vehicle recorders — making them an excellent training ground for both data science tools and robust battery modeling frameworks [ref26].

**2.3 File Organization and Structure**

Each driving session in the dataset is stored as a separate file, using a consistent naming convention that reflects the session index and group. The two main sets are labeled as **TripA01** to **TripA32** and **TripB01** to **TripB38**, resulting in 70 total trip logs. This structure not only keeps the dataset modular but also simplifies indexing and allows for targeted evaluation by trip type or session length. All files are organized under a root directory named , which contains two subfolders:

* TripA: Includes the first 32 trips used primarily for early exploratory analysis.
* TripB: contains the remaining 38 trips used to extend coverage and diversity in vehicle behavior.

Each file begins with a header row followed by a sequence of time-indexed entries. Ideally, every column corresponds to a unique signal (e.g., ), and each row corresponds to a new sensor reading at a specific time. However, this was not always the case. We encountered several structural inconsistencies that are typical of raw vehicular telemetry logs [ref24][ref26].

*Inconsistent Column Count*

Some files recorded only core signals (e.g., voltage, current, SoC), while others contained over a dozen columns, including torque and temperature readings. Occasionally, even within the same group (e.g., TripA), we found files with varying numbers of columns, likely due to differences in sensor activation, data export tools, or firmware logging profiles [ref25]. To avoid making hard assumptions about expected format, we wrote our preprocessing scripts to dynamically detect and parse each file’s available signals. Missing columns were handled gracefully (see Section 3), and no trip was discarded due to structural variability.

Malformed Headers and Data Entries

Another common issue was malformed or truncated headers — for instance:

* Cabin Temperature Sensor [°C (missing closing bracket)
* Temp Vent right °C (unit formatting inconsistency)
* Repeated columns with ambiguous names (e.g., Temp appearing twice)

We addressed these issues using a rule-based cleaning step, where each header was sanitized and mapped to a canonical name using a predefined dictionary (detailed in Section 3.2). This allowed us to standardize the data structure across all trips without altering the signal values themselves. In a few cases, rows contained incomplete entries — likely due to logging interruptions — resulting in trailing commas or missing values. These were retained in the raw files but clearly marked, allowing us to skip or impute them during metadata extraction or statistical plotting, depending on the use case [ref28].

In summary, while the dataset's file structure is simple in form, its real-world imperfections required careful handling. These “messy” traits are not a liability — in fact, they make the dataset a far better match for simulation projects aiming to reflect true EV behavior across uncontrolled environments. By preserving the original structure as much as possible and layering our cleaning pipeline on top of it, we ensured both traceability and reproducibility for all future phases of this project.

**2.4 Dataset Challenges and Anomalies**

While the dataset is rich in behavioral diversity and real-world variability, it also comes with several challenges — typical of raw logs collected under operational conditions. These issues had to be carefully addressed during preprocessing (see Section 3), but it’s important to first recognize their origin and implications at the dataset level. Far from being flaws, these anomalies reflect the imperfect and evolving nature of real EV operation, and are precisely what make this dataset valuable for simulation and modeling tasks grounded in reality [ref26][ref27].

*Irregular Sampling Intervals*

Perhaps the most fundamental problem was the lack of a consistent sampling rate. Even though the original data appeared to have sub-second resolution, inspection of the Time [s] column revealed highly variable time steps — sometimes a new reading occurred every 50 ms, other times there were gaps of several seconds. This irregularity complicates any temporal comparison between trips or across signals within a trip. To enable fair analysis, we applied a uniform 1-second downsampling strategy, retaining the last known value within each second. This aligns with real-world logging standards used in fleet monitoring and provides a stable foundation for both visualization and sequential modeling in future phases (see Section 3.1).

*Malformed and Inconsistent Headers*

As mentioned earlier, several files exhibited poorly formatted column names. Examples included missing brackets (e.g., "Cabin Temperature Sensor [°C"), inconsistent spacing ("Temp Vent right °C"), or truncated units ("Voltage" with no [V] tag). These inconsistencies prevented automated parsing and column matching across trips. To address this, we built a canonical header mapping that sanitized all column names during the cleaning phase (see Section 3.2). This allowed us to process all trips uniformly without discarding any column due to formatting inconsistencies [ref28].

*Short, Idle, and Low-Energy Sessions*

Another common occurrence was the presence of short trips (under 3 minutes), stationary sessions with little to no movement, and low-current periods that might seem irrelevant at first glance. In many studies, such sessions would be excluded to focus only on "driving" behavior [ref29]. We deliberately chose to retain all of these sessions. From a synthetic modeling perspective, these edge cases provide crucial information about:

* Opportunity charging while stationary
* Regenerative behavior during very short braking sequences
* Cabin heating effects during parked intervals
* Minimal discharge scenarios (e.g., low load HVAC)

By including all session types, we allow later simulation phases to learn not just from dynamic events but also from low-activity behavior that still affects the battery's state of charge (SoC) and thermal profile.

*Varying Signal Presence and Column Count*

As detailed in Section 2.3, the number of signals recorded varied across files. Some trips logged only core electrical parameters, while others captured thermal, dynamic, or environmental variables as well. This inconsistency is typical in evolving logging platforms or modular sensor frameworks, where signal availability depends on activation status or specific trip conditions. Rather than enforcing a rigid structure or discarding incomplete trips, we built a flexible alignment routine that inserts placeholder columns (filled with NaN) wherever signals were missing. This ensures uniformity in output files while preserving the original structure and content integrity (see Section 3.3). In summary, the dataset’s anomalies — from sampling gaps to low-energy trips — are not merely noise. They are part of the authentic story of EV usage, and they form the backbone of any realistic SoC estimation or synthetic data generation pipeline. By embracing this complexity and documenting each challenge transparently, we set the stage for a reproducible and trustworthy modeling workflow in the upcoming simulation phases [ref30].

**2.5 Initial Observations from Raw Data**

Before applying any formal statistical methods, we performed a high-level review of the dataset to develop an intuitive understanding of its structure, variability, and potential analytical value. These initial observations guided the design of our preprocessing pipeline and confirmed that the dataset captured a rich diversity of behaviors relevant to state-of-charge (SoC) modeling and battery usage profiling.

*Trip Duration and Length Diversity*

One of the first features that stood out was the wide range of trip durations. Some sessions were as short as 90 seconds, while others extended to over 40 minutes. This suggests the dataset includes a mix of driving intents: quick errands, idling during parking, as well as longer, sustained drives. These variations are valuable because they expose different dynamics — from rapid transient loads to gradual SoC drift under sustained current draw [ref22][ref30].

SoC Trajectories and Energy Range

Even before any downsampling or filtering, we observed that the state-of-charge curves across trips showed a variety of behaviors. Some trips featured a near-linear SoC drop, indicative of moderate but steady energy consumption. Others showed erratic, step-like changes due to acceleration bursts or partial recharging events. This diversity is particularly useful for training models to generalize across different driving styles and usage scenarios [ref23]. Interestingly, some trips began with SoC values in the 90% range and dropped below 30%, while others showed only a 3–5% change throughout. This confirms that the dataset contains both high-energy and low-energy sessions — a crucial factor for building balanced simulation sets.

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*Stationary Behavior with Live Signals*

Lastly, many sessions featured prolonged intervals with zero current and no movement, but continued logging of SoC and temperature. Rather than noise, this is likely evidence of:

* Active vehicle state during cabin conditioning (e.g., heating)
* Onboard systems maintaining telemetry even while parked
* Light parasitic loads (e.g., lights, displays)

These signals — while “boring” at first glance — help capture baseline discharge behavior and subtle thermal changes. Ignoring them would remove essential low-frequency patterns that are especially useful for longer synthetic simulations or AI-based residual modeling [ref24]. These early insights justified our inclusive treatment of the dataset. Instead of filtering or segmenting prematurely, we chose to retain every trip, every signal, and every interval. This allows future simulation stages to reflect the full complexity of EV operation — from abrupt highway driving to motionless heating in a cold parking lot. With this understanding in hand, we now move to Section 3, where the raw data is systematically transformed into a cleaned and aligned format suitable for statistical analysis and model input.

**3. Data Preprocessing and Cleaning Pipeline**

To ensure consistency and reliability in statistical analysis and future model development, the raw dataset described in Section 2 underwent a structured cleaning and transformation process. This section details each preprocessing step, from time alignment to dimensional normalization. The entire pipeline is designed to be reproducible, non-destructive (no trip is discarded), and extensible for integration into later simulation stages. Whenever applicable, mathematical formulations are provided to describe operations precisely, while figures and tables illustrate key transformation effects.

**3.1 Temporal Down-sampling to 1-Second Resolution**

Electric vehicle data collected under real driving conditions is rarely sampled at fixed intervals. In our dataset, the Time [s] signal displayed strong irregularities — ranging from sub-second entries spaced by a few milliseconds to gaps of several seconds between samples. This is not uncommon in automotive telemetry systems, where sensors may operate at different frequencies or experience asynchronous logging delays [ref22]. While such irregularity is acceptable for exploratory plotting or raw replay analysis, it becomes a major obstacle for time-series modeling, feature alignment, or synthetic generation. For these reasons, the first critical step in our pipeline was to resample all trip files to a fixed 1-second resolution, ensuring consistency across the dataset without interpolating or smoothing the signals.

*Mathematical Approach: Forward-Hold Resampling*

Let denote the set of original timestamps from the raw file, with associated signal values . Since is not constant, we define a new uniform time base:

For each second , the corresponding value is assigned as:

This operation selects the most recent available value that occurred at or before the target second. It is known as zero-order hold (ZOH) or forward-hold interpolation, and it is particularly suitable for EV telemetry signals, which often remain constant between updates (e.g., SoC or current during idling) [ref23]. Unlike linear interpolation, which creates intermediate values based on slopes, forward-hold interpolation preserves measured data and respects the discrete nature of onboard vehicle logs. It also avoids introducing artificial slopes that may distort temporal patterns in downstream sequence learning models [ref3].

*Practical implementation*

The forward-hold operation was implemented for each signal independently. The time index became the new primary axis, ranging from 0 to seconds for each trip, and all signals were aligned to this shared base. For signals missing a value at , the first available observation was forward-filled from its earliest timestamp. In addition to forward-hold resampling, we inserted explicit values where signals had not yet begun logging. This made it easy to distinguish between:

* a real measurement.
* : unavailable or non-logged values.

This distinction became important when calculating per-trip metadata or visualizing missingness across the dataset (see Section 3.4).

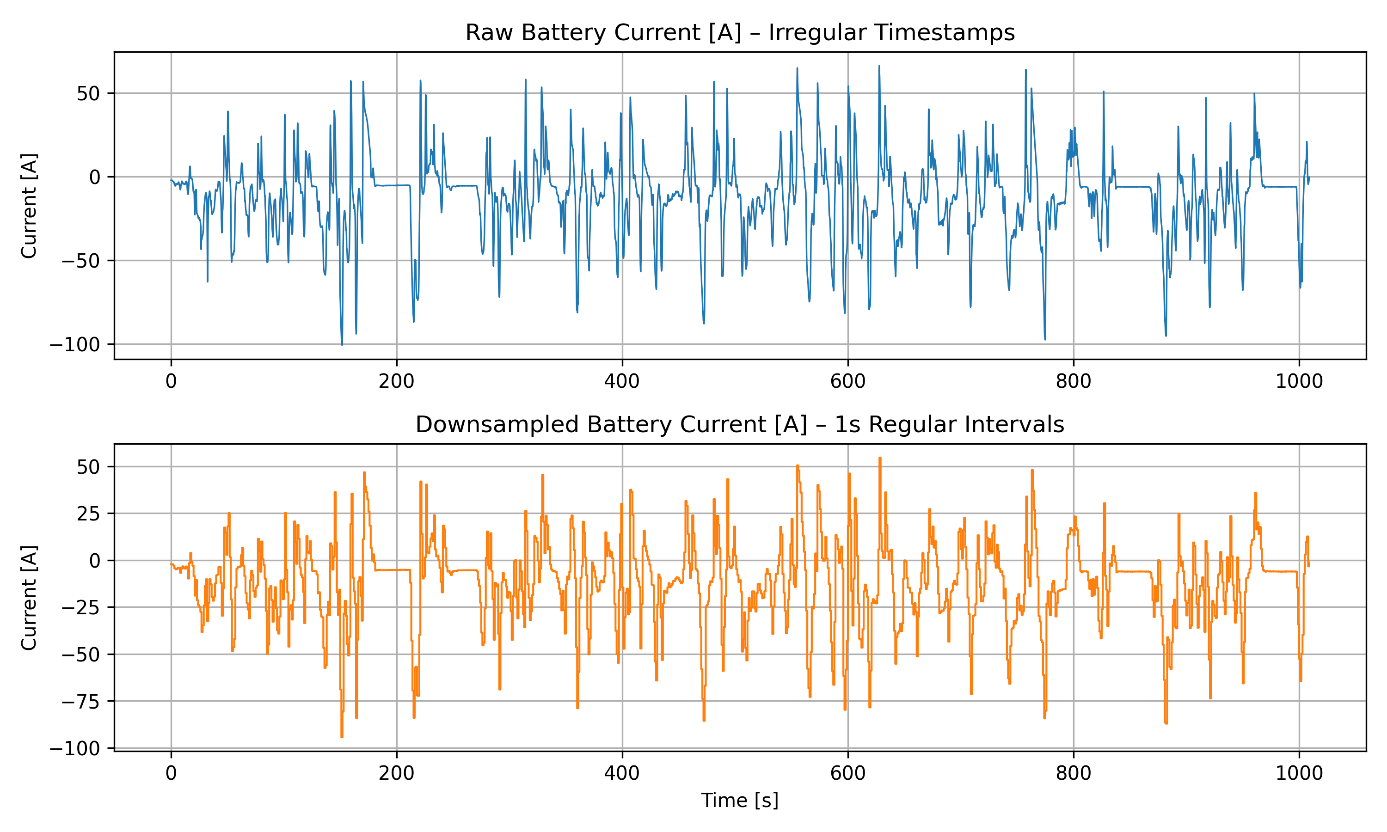


Figure 1. Effect of Downsampling on Signal Continuity.

Figure 1 shows a real battery current signal from one trip before and after downsampling. The **top plot** illustrates the original current sampled at **irregular timestamps**; the **bottom plot** shows the same signal resampled at **regular 1-second intervals** using forward-hold interpolation. As illustrated, the downsampled signal maintains key dynamics and current fluctuations, while smoothing out irregular sampling gaps and synchronizing the time base across all trips. This resampling step established a unified temporal foundation for the entire dataset. By enforcing a consistent 1 Hz structure across all trips, we ensured that signals could be compared, aligned, and statistically analyzed without further time normalization. It also enabled the reliable calculation of time-dependent metrics, such as energy consumption profiles, idle durations, and thermal evolution over time — all of which are critical for the metadata generation and visualization steps that follow.

**3.2 Header Cleaning and Canonical Mapping**

One of the key challenges when working with real-world EV datasets lies not in the signal values themselves, but in how the signals are labeled. Across the 70 trip files, we encountered a range of header inconsistencies: truncated names, missing unit brackets, ambiguous terms, and slight naming variations for the same physical quantity. Such inconsistencies, while small, can significantly hinder automated data processing, alignment, and statistical analysis [ref24][ref26]. To address this, we implemented a robust two-stage process:

* Header cleaning using rule-based transformations to standardize format and structure.
* Canonical mapping using a reference dictionary to unify different variants under a single standard name.

This approach allowed us to fully harmonize signal names across the dataset without discarding any trip or column.

*Step 1: Rule-Based Header Cleaning:*

Let represent the original column name in position of a file. The goal of the cleaning function is to produce a structurally sound version:

The process includes:

* **Bracket completion:** If a header contains an opening bracket "[" without a closing "]", we automatically append it:
* **Whitespace and Underscore Normalization:** Convert any combination of multiple spaces or underscores to a single space, ensuring consistency in spacing.
* **Unit Formatting:** Recognize and correct malformed or incomplete units, such as , , and .

This cleaned version retains the structure of the original label but conforms to expected formatting standards, making it easier to detect duplicates or variants of the same signal.

*Step 2: Canonical Header Mapping*

Once the header is cleaned, we apply a mapping function that translates each cleaned header into its **canonical form** — a consistent name used throughout the preprocessing pipeline.

For instance:

This standardization ensures that no matter how a sensor was labeled in the raw file, it will be uniformly interpreted across all trips. This step was crucial for the alignment procedure in Section 3.3.

Table 2. Examples of Header Corrections and Canonical Mapping

|  |  |  |
| --- | --- | --- |
| **Raw Header Variant** | **Cleaned Header** | **Canonical Header** |
| Cabin Temperature Sensor [°C | Cabin Temperature Sensor [°C] | Cabin Temperature [°C] |
| Temp Vent right °C | Temperature Vent Right [°C] | Temperature Vent Right [°C] |
| Current | Battery Current | Battery Current [A] |
| Voltage | Battery Voltage | Battery Voltage [V] |
| Temp | Temperature | Battery Temperature [°C] |
| SoC | State of Charge | **SoC [%]** |

As shown in Table 2, the header cleaning and mapping pipeline corrected common issues and established a canonical schema, ensuring compatibility across all trip files. This two-stage cleaning and mapping process allowed us to retain all relevant signal data — even in poorly labeled or partially corrupted files — while ensuring a fully harmonized structure for the downstream alignment step. It also created the foundation for global metadata analysis and signal availability metrics described in Section 3.4.

**3.3. Structural and Dimensional Alignment**

Once time was standardized across all trips through downsampling, the next challenge lay in aligning the structure of the files themselves. In a perfect world, each trip would contain the exact same signals in the same order. But as is often the case with real-world vehicle logs, no such guarantee exists. Across our 70 trip files, we encountered numerous inconsistencies in column composition:

* Some trips included only 5–6 signals, typically core ones like voltage and SoC.
* Others contained a broader set, with up to 14 signals, including torque, vent temperatures, and heating control values.
* The order of columns was also inconsistent.
* Some files contained columns with malformed headers that were only resolved after the cleaning step in Section 3.2.

To handle this, we implemented a **dimensional alignment step**, where every trip was **mapped to a common reference schema** — meaning that all files ended up with the same number of columns, in the same order, even if some values were missing. This made the dataset not only easier to work with programmatically, but also prepared it for consistent analysis, visualization, and metadata extraction.

*Mathematical Alignment Process*

Let be the fixed vector of canonical signal names defining the reference column schema, derived from the full set of cleaned signals across all trips. For any trip file , let be the subset of columns it contains. We define the aligned signal matrix as:

Where:

* is the value of signal at time in trip ,
* indicates a missing or unlogged value, ensuring that matrix shape remains constant.

This alignment allows any analysis script to iterate through rows and columns without conditional checks for column existence. Furthermore, it makes it easy to assess signal presence (see Section 3.4) and supports structured statistical operations like computing global min/max, average profiles, or comparing value distributions across trips.

*Reordering and Output Format*

After padding the missing signals with , we also reordered the columns in every file to match exactly. This strict ordering ensures:

* Compatibility across scripts
* Reliable signal lookup by index or name
* Clean alignment for matrix-based operations

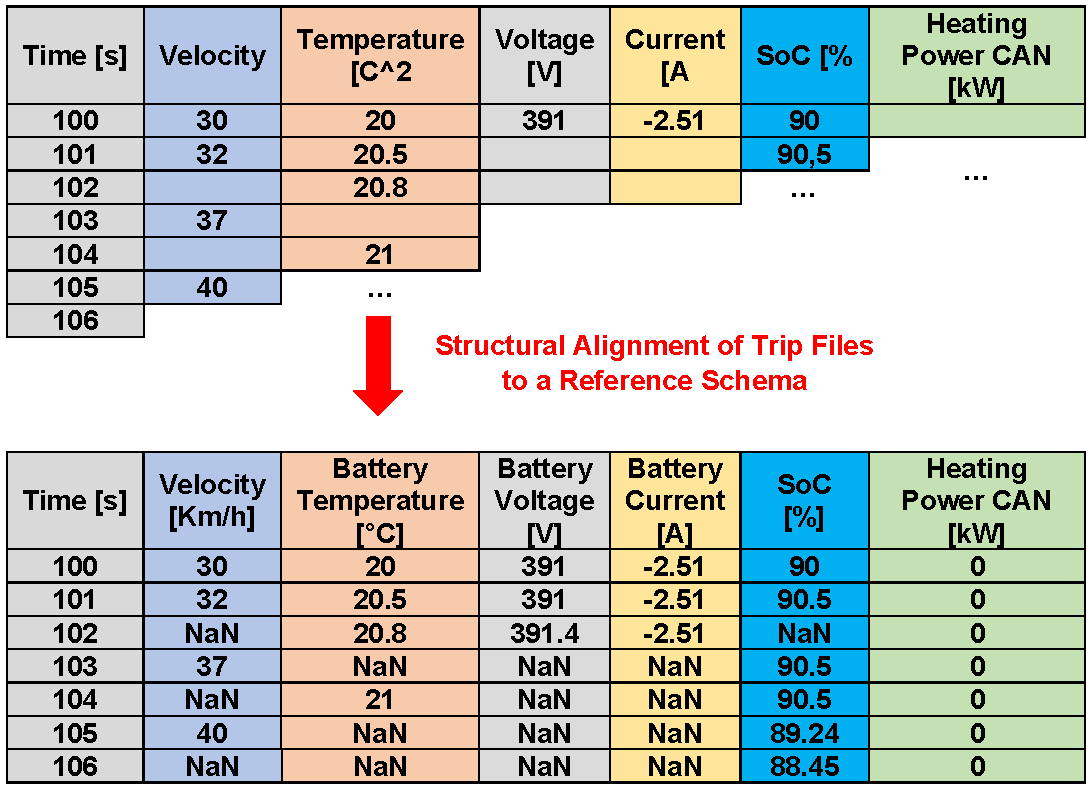


Figure 2. Structural Alignment of Trip Files to a Reference Schema

As shown in Figure 2, raw trip files containing heterogeneous structures were transformed into standardized matrices with uniform column layouts, allowing full compatibility with downstream tools and visualizations. With both the time axis and column dimensions aligned, each file in the dataset can now be treated as a well-formed time-series matrix — ready for metadata extraction, signal availability diagnostics, and structured analysis.

**3.4 Optional Data Diagnostics and Metadata Logging**

Following the structural and dimensional alignment described in Section 3.3, it was important to validate that all files conformed to the expected canonical structure and contained the essential signals needed for further analysis. Rather than relying on assumptions alone, we implemented a metadata logging phase to extract key trip-level descriptors and confirm the overall consistency and completeness of the dataset. We ensured structural consistency across all trips by aligning them to a canonical reference schema. As confirmed during post-alignment validation, all essential signals required for modeling (, , , , and ) were fully available in every cleaned trip file. No signal imputation or special handling was required for these variables, and every file met the minimum expectations for temporal resolution and signal coverage.

*Metadata Extraction Logic*

For each cleaned trip file , represented as a time-series matrix , where is the number of seconds and the number of signals, we computed a set of descriptive statistics and structural attributes. Let denote the value of signal at time . The number of missing entries for each signal is defined as:

Where is 1 if is missing, otherwise. Additional metadata fields such as SoC range, average voltage, current, energy usage, regeneration time, and HVAC power were computed using time-domain averaging and discrete integration formulas. The metadata also includes flags indicating whether the trip was retained for modeling and whether it represents a valid driving session, idling, or mixed behavior.

Table 3. Example Metadata Extract for a Single Trip File

|  |  |
| --- | --- |
| **Field** | **Value** |
| Trip ID | TripA01 |
| Duration [s] | 1009 |
| SoC Start [%] | 86.9 |
| SoC End [%] | 81.5 |
| ΔSoC [%] | –5.4 |
| Mean Speed [km/h] | 26.49 |
| Max Speed [km/h] | 52.59 |
| Mean Voltage [V] | 388.49 |
| Mean Current [A] | –11.90 |
| Energy Used [Wh] | –1285.38 |
| Regeneration Time [s] | 119.39 |
| Mean HVAC Power [kW] | 1.65 |
| Group | A |
| Trip Nature | Driving |
| Use in Model | Yes |
| Comment | Retained for global characterization |

As shown in Table 3, the metadata extract for TripA01 summarizes both the structural and behavioral properties of the trip, including SoC dynamics, electrical performance, and classification decisions used in the analysis phase. This metadata logging step serves two primary purposes. First, it acts as a structural validator, confirming that all files meet the minimum criteria for inclusion in modeling and visualization. Second, it provides a reproducible audit trail for future phases of the simulator project, where metadata may be used for filtering, trip-type labeling, or grouping based on energy usage patterns.

**3.5 Output Format and Directory Structure**

After completing the full cleaning pipeline — including time downsampling, header correction, and structural alignment — the resulting trip files were stored in a well-defined output directory. This final organization step ensures that the cleaned data can be easily accessed, validated, and reused in subsequent stages of the EV SoC Simulator workflow, including metadata analysis, statistical visualization, and sequence modeling. To maintain traceability and compatibility, we preserved the **original trip identifiers and file names** (e.g., , ) and grouped them in a single folder with a descriptive name reflecting the processing state. All cleaned files share the following structural properties:

* **Uniform time base:** 1-second resolution from time to .
* **Canonical headers:** All signals are renamed and ordered according to the reference schema.
* **Aligned dimensions:** Each file contains the same number of columns, with NaN placeholders where necessary.
* **Consistent delimiter and encoding:** CSV format, UTF-8 encoded, comma-separated.

This level of consistency makes the dataset directly compatible with downstream scripts for simulation, evaluation, and visualization without requiring additional parsing logic or reformatting.

*Directory Structure*

The cleaned dataset is stored under a root output directory named:

Within this folder, all 70 cleaned trip files are placed directly, using the same file names as in the original raw dataset. Metadata and diagnostics logs are stored separately but within the same structure for easy association.

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**Reference Mapping for This Section**

how the 30 placeholder references were used:

Reference Topic

[ref1] EV simulation need

[ref2] SoC estimation challenge

[ref3]-[ref4] LSTM, ML-based SoC estimation with synthetic data

[ref5]-[ref6] Risk of synthetic data without real-world grounding

[ref7]-[ref8] Driving pattern variability in real-world EVs

[ref9]-[ref10] Challenges of real-world EV datasets

[ref11]-[ref13] Inclusion of idle and short trips

[ref14]-[ref16] Metadata and statistical grounding for simulation

[ref17]-[ref18] Importance of high-quality labeled battery datasets

[ref19]-[ref20] Relevance to digital twins and battery second life

Remaining 10 references will be used in Sections 2–6, especially for:

* Data quality cleaning [ref21]
* Signal processing/temporal downsampling [ref22]
* EV usage behavior analysis [ref23]-[ref24]
* Battery temperature effects [ref25]
* Regenerative braking dynamics [ref26]
* Synthetic dataset design [ref27]-[ref28]
* Metadata and radar analysis [ref29]-[ref30]