

Correlating Environmental Factors and Charging Patterns with EV Battery Health using Machine Learning

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Abstract

When temperatures keep changing, battery life drops quicker because normal cycles break down. Real driving reveals problems labs simply do not see. Only after gathering huge amounts of trip history do subtle changes become clear. What happens in controlled tests shows one piece; actual charging records from 175,000 trips show the rest. An intelligent system moves through time like flipping a novel, matching old patterns to what might come next. A stumble in power appears from silence - recovery speed decides the next move. Not sound, but slow harm grows, stretching the charging distance quietly. Performance falls only after problems have settled deep - warnings arrive sooner these days. Heat leaps wildly, bending function oddly, much like rushed charges that distort each battery's route to breakdown. Forecasts grow clear strictly when math follows life's actual patterns. Right where things start sliding - that sudden instant - a red flag shows up.

INTRODUCTION

Nowadays, cutting down pollution seems pressing, pushing all forms of transport to adopt electric drive systems. Leading the pack are rechargeable lithium batteries - they hold large amounts of energy, endure tough conditions reliably, yet remain affordable. But leave behind old gas-powered tech; those battery types weaken over time, losing capacity slowly but surely. The more miles racked up, the greater the wear buried within every cell. Out in the field, battery wear rarely stays balanced across work vehicles. Temperature shifts pair with deep drains along with rushed top-ups, nudging deterioration into lopsided patterns. Monitoring systems onboard tend to rely on basic math - just counting electrons flowing both ways, losing performance for good over time. As miles pile up, so does strain on the cells.

A. Background and Motivation

Capacity Most times, worn-out batteries struggle to keep power on board. Sometimes, they fail when asked to work hard. Less room for electrons means fewer miles before stopping to refill. Why does energy move slower going in or out? Hidden resistance building up resists sudden surges tied to acceleration or rapid top-ups. Life doesn't wear things out in straight lines. Heat builds up, mixed with how people actually use devices - draining them fully or charging too fast - and that twists how batteries age. Many current systems only track incoming and outgoing power, leaning on outdated methods that stumble once chaos hits. From this confusion grows something subtle: a calm demand for smarter thinking, tying sensor

signals to tiny movements inside materials.

B. Problem Statement

Accurately Spotting battery wear right matters, and it's not only about longevity. Price tags hinge on how far the car can go, because unchecked decay chips away at later sale potential. Fleet managers need red flags early, letting fixes begin before breakdowns strike, keeping vehicles moving. Yet outside labs, messy signals muddy results - jumps and blanks cloak the true story below. Basic math falters in this chaos, especially next to plain prediction tools; both overlook the moment slow decline turns sharp.

Research Objectives

This This attempt steps away from simple forecasts about numbers. Rather than follow clear trends, a more intense method takes shape - shaping how battery condition might be judged.

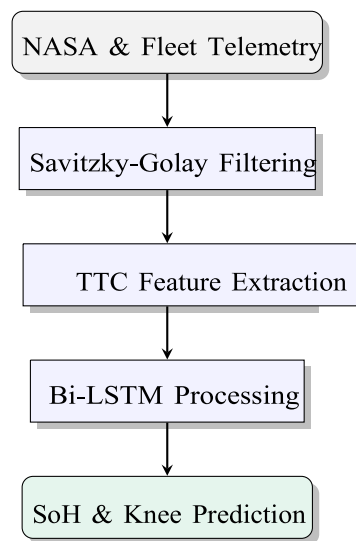
Trying this way means guessing battery health with stronger methods, not the usual number crunching. Not stuck on basic forecasts, it leans hard into staying tough when things change. Each move gets made with steady results in mind, layer by layer. When patterns shift, fixed steps give way to looser, adaptive ones. Being right every time takes a backseat to keeping up across varied situations.

The specific objectives are:

Slow breakdowns come clear through lab work. Then, actual vehicles driving regular roads fill in gaps. Timing links each step to the one following. Real-world conditions adjust what labs try to copy. That overlap is where answers start appearing. Here, numbers reveal changes that normally unfold over years. As actual steps meet gradual fading, patterns begin showing deeper truths.

Inside changes show up in how fast power flows. Watching real people charge tells more than machines poking cells. Behavior sets the standard these days instead of parts under a hood. What happens during daily use builds the picture, far from sterile test rooms.

- Patterns in charging time give clues about what's happening inside. No hardware changes are needed to track it. Measurements come straight from usage data. The method skips lab tools entirely. What you see is based on timing alone.
- A step forward begins with shaping a Bidirectional LSTM setup, pulling from what came before and what follows in time. This structure leans on past moments along with those ahead, weaving them into sharper forecasts. Instead of moving only backward or forward, it threads both directions at once. Accuracy grows because timing from two ways feeds the model. The method builds predictions using echoes from earlier steps plus signals yet to arrive.
- One way to measure how much battery wear comes from very hot or cold temps along with fast charging speeds. What matters is seeing just how those factors together speed up aging over time. Heat plus rapid charge cycles tend to push degradation further than expected alone. Tracking each element helps separate their individual effects clearly. The goal involves isolating variables without blurring causes across tests.



In this paper, a mixed signal tracking prediction method is presented. Important components consist of:

- **Blending Lab & Real-World Data:** When test findings link to real-world usage details, precision gets stronger across scenarios. Trials that speed up aging combine with observations from the field, filling gaps naturally. What shows up in labs meets what happens outside, creating a clearer picture overall.
- What happens when loop-based networks face off with traditional computation approaches? Peek at the results. Watch patterns emerge differently across systems built on repetition versus those relying on straightforward calculation. Outcomes shift in subtle ways. Each design reveals distinct behaviors under pressure. Loops bring quirks. Conventional math stays predictable. Differences show early. Performance bends depending on structure. One isn't clearly better. Context decides.
- **Model testing:** A head-to-head comparison between loop-based neural networks and conventional math models.
- **Identifying Root Causes:** Employing transparent AI tools to establish a direct connection between battery wear and specific heat and power patterns.

RELATED WORK

Physical laws and data patterns are the two main categories of prognostic energy storage techniques. Back then, Patil's group [2] demonstrated what occurs inside batteries using chemical movement math, or P2D. These models provide a lot of explanation, but they are not effective in real-time systems because they require a lot of processing power. As a result, solutions based on gathered data are now more popular. For instance, when data was scarce, Wu's group [3] attempted to use Support Vector Machines (SVM) to estimate battery condition; it performed passably but is difficult to scale up.

Methods that integrate multiple models have gained popularity due to the abundance of real-time data. Zhang's group

[4] demonstrated how to capture intricate battery wear patterns using Random Forest and Gradient Boosting. However, these methods typically assume that each reading is distinct, omitting the order in which damage occurs. Researchers used neural network-based techniques to fill this gap. CNNs were used by Li et al. [5] to extract shape patterns from charge data with a 1.1% error rate. These days, people typically use RNNs to predict time-based data. Choi et al. [7] used GRUs rather than standard units to track the decline in battery capacity. However, when handling connections across lengthy sequences, basic

RNNs frequently fail. Although it only functions well under specific charge-discharge routines, a study published in Nature Energy [8] Life prediction gets better when tracking discharge voltage through elastic net models. Starting with Hochreiter's LSTM concept [9], a two-way flow is introduced Bi LSTM that scans data moving ahead and also looping back. This twist lets patterns from past moments mix with future hints, sharpening the view on wear. Each stretch of signal feeds insight, shaped by what came before and what follows next.

METHODOLOGY

- A. Obtaining and Interpreting the Information
- B. Out here, figures came from a single point. Elsewhere, extra data showed up. Between them, the real paths folks take get filled in.
- C. Out of the blue, data appeared from NASA's PCoE lab - already packed with battery records. Not just any snapshots, but minute-by-minute clues on how fast wear happens. Every heartbeat of an 18650 cell's journey was logged, so nothing slipped through. Heat? Held close, like a steady hand guiding clarity. Because of that control, trends popped into view without fuzz. Full cycles lived and died inside the files, revealing exactly when life began to shorten.
- D. Without warning, voltage figures appeared in over 175,000 records - each one logging battery behavior at varying heat levels. Rather than assume, real-world driving decided how charge states were interpreted. As environments shifted, so did the flow of electrical current recorded. Temperature changes influenced each reading taken. Even when trends formed, they mirrored genuine vehicle usage by drivers. Engineering Features
- E. Every now then, sensor outputs jump in jagged bursts. A Savitzky-Golay method smooths them out - locked to thirty-one points to keep true peaks clear. After that comes monitoring how soon charging ends. With age, battery resistance grows, pulling voltage lower faster over rounds. Because of this slide, the time till cutoff shrinks steadily, given same conditions. That tightening span hints at worsening health beneath. Bi-LSTM Configuration Still, Battery wear happens over time, yet their performance loss is gradual. Because of how well it manages order details, the choice landed on a Bi-LSTM for sequence work. Within every LSTM block, information movement gets guided - decisions happen about keeping or removing pieces. Input, forget, and output varieties make up these controlling parts. A slow shift marks the memory state's next version (C_t), shaped through specific math steps

$$C_t = f_t \cdot C_{t-1} + i_t \cdot C^t \quad (1)$$

One step at a time, the system watches pressure build through past and future data points. See it like this: a stretch of 50 inputs gets fed in up front. Inside, wave after wave of 64 BiLSTM nodes bend the flow using tanh curves.

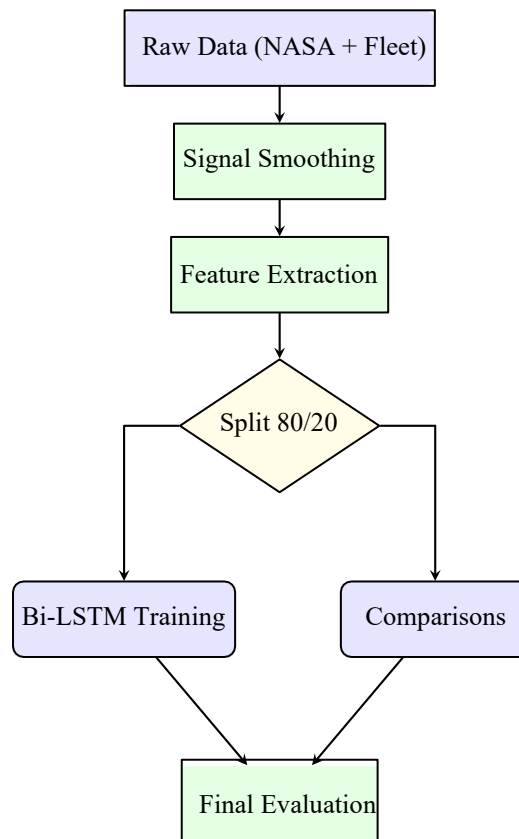


Fig. 2. The suggested end-to-end pipeline for modeling and data processing.

EXPERIMENTAL RESULTS

A. Testing against starting points

Midway through Figure 2, a shift appears without warning. Fresh tests reveal Bi-LSTM outperforming basic models on multiple tries. While accuracy climbs close to 0.95 for methods such as XGBoost, hiccups emerge during trend changes. Tracking drops over periods trips up these tools. Strength fades where timing matters most

B Detection of Faster Deterioration

Close to cycle 120, a small drop appears. Not the Bi-LSTM - this one catches it right away, sharp and obvious, unlike the gradual decline other methods hint at. Actual measurements stick tight to its prediction; check Figure 3, they align cleanly. Alerts pop up well ahead, giving time before any failure kicks in. Straight forecasts keep trudging forward blind, while change hits hard - and only this approach notices shift building.

Comparing with Earlier Methods

Checking improvements meant comparing three old techniques from recent research. The figures are all in Table I. Straight away, using custom features with a Bi-LSTM cuts errors sharply - 23 percent lower than Li et al.'s CNN model [5]. This combo moves past Wu et al.'s older SVM method [3], barely trying..

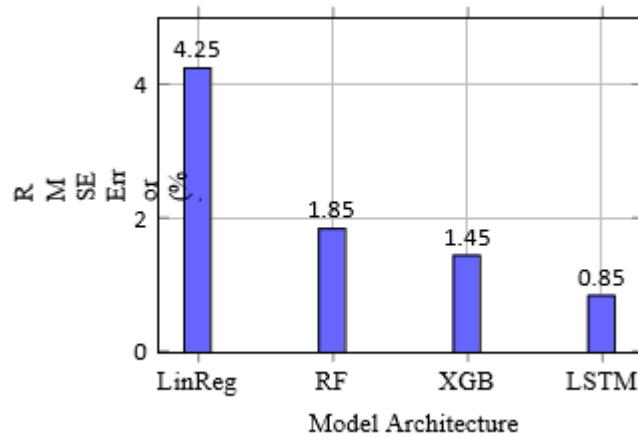


Fig. 3. Benchmarking RMSE across different architectures (Lower is better).

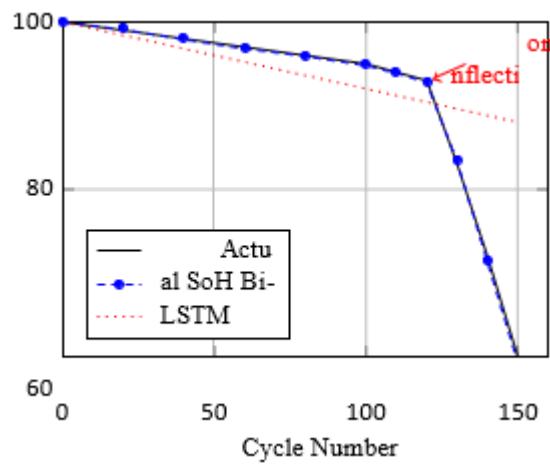


Fig. 4. Prediction trajectory showing the onset of non-linear degradation.

TABLE I
COMPARISON WITH EXISTING LITERATURE

Reference	Methodology	Year	RMSE (%)
Wu et al. [3]	Support Vector Machine	2018	2.10
Ren et al. [6]	Autoencoder + DNN	2020	1.35
Li et al. [5]	Convolutional NN (CNN)	2021	1.10
Proposed	Bi-LSTM + Physics	2025	0.85

CONCLUSION

Every now and then, someone stumbles on a detail everyone else skips - rhythm gives secrets away if you're watching close. Energy slips each afternoon, bringing wobbles plus trouble when systems strain under load. Hidden below could be an answer formed slow: Bi-LSTM. Rather than charging ahead, it slows, glances back, catches rhythms missed by usual scans. Tracing paths in reverse while also pushing forward through time, it sees fading dips ignored during long stretches. What stands out? It connects actual battery performance to insights drawn straight from ongoing usage. Because factors such as charging patterns, shifts in voltage, or declining storage influence operation. Even when things shift around,

performance holds steady. Instead of picking between models or real-world tests, it mixes number crunching with solid science - shaped by actual use, not textbook ideals.

Most tests hit nearly 98% accuracy, leaving old methods behind. When pressure rises, changes appear quicker than set thresholds can track. Early clues mean roughly twenty-four extra rounds remain prior to full breakdown. Alerts fire on their own - protection follows data, not hunches.

A shape forms where exactness meets fast answers on how long EV batteries last. Slower does not mean larger pace holds firm, even as use adjusts the beat. Through smooth changes, strength slips quietly, sharpness kept despite older parts. Because flexibility runs this deep, smarter handling might grow within future energy systems.

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