

Proactive Early Warning for EV Battery Packs: A Concept Note on Reading the Recovery Speed of the BMS Voltage Signal

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Abstract. The battery management system of an electric vehicle records cell voltage, current and temperature many times a second. Every current method that uses these signals to detect degradation is either reactive, acting after a fault code is raised or a capacity threshold is crossed, or trained, requiring labelled examples of degradation events to build a model. This note proposes a proactive layer that needs neither. It watches how quickly the small, cycle-level voltage fluctuations return to their normal level after each disturbance. In a healthy cell this return is fast. As the cell approaches a tipping point, the return slows, and this slowing can be seen in the signal before any threshold is crossed. The slowing is measured by the lag-1 autocorrelation of the voltage residual within a rolling window. When this statistic rises persistently towards 1, a graded shunt acts on the entities of the BMS domain, adjusting the charge rate, flagging the cell, or pausing the charge, before the cell crosses a danger line. The shunt is the core of the invention. The lag-1 autocorrelation as an early warning signal rests on well-established physics [1, 2]. The application of a graded shunt to the BMS domain, triggered by the statistic rising persistently towards 1, is what this note proposes. It is a concept note. No battery data have been analysed. The method is patent pending.

1 The Problem with Every Current Approach

An EV battery pack degrades gradually. The capacity falls slowly over hundreds of cycles, and then, at the knee point, it falls rapidly [3, 4]. The knee point is hard to predict because the cell gives no single clear signal before it arrives. Every current approach tries to address this, and every current approach has the same structural limit: it reads what has already happened.

The two designs, set out separately:

- **Today's systems:** a fault code fires, a capacity threshold is crossed, or a trained model predicts from past data. The response comes after the signal has already changed.
- **This note (proactive):** reads how quickly the voltage returns to its cycle-level baseline after each small disturbance. When the return slows persistently, the shunt acts before any threshold is crossed.

2 How Each Existing Approach Differs from This One

The table below sets out each approach found in the literature on one line, followed by this note on its own line.

Approach	What it reads	Training?	Acts before threshold?	Shunt on BMS?
Fault-code monitoring [5]	BMS fault flags, after event	No	No — reactive	No
Capacity fade tracking [3,4]	Capacity per cycle, after cycle	No	No — at threshold	No
dQ/dV curve analysis [6]	Differential voltage features, after cycle	Some variants	Partial — near threshold	No
Machine learning on BMS [7]	Voltage, current, temperature features	Yes — labelled data	Partial — model-dependent	No
Deep learning / physics-guided [8]	Multi-sensor fusion	Yes — supervised	Partial — trained on events	No
Knee-point prediction [9]	Degradation curvature, many cycles	Some variants	Partial — needs history	No
Impedance spectroscopy [10]	Electrochemical impedance	Partial	Partial	No
This note	Recovery speed of voltage residual, within each cycle, at run time	No	Yes — before any threshold	Yes — graded, on BMS domain only

3 The Physics: Critical Slowing Down

In many physical and chemical systems, a slowing of recovery after small disturbances appears before a tipping point. Scientists call this critical slowing down [1, 2]. As a system approaches a tipping point, its restoring force weakens. Small perturbations that would normally fade quickly now take longer to fade, and each reading starts to look more like the one before it. The clearest mathematical sign is a rise in the lag-1 autocorrelation of the signal's residual.

The lag-1 autocorrelation as a warning signal is well known from ecology, climate and engineering [1, 2, 11]. This note does not claim it. What this note proposes is its application to the BMS voltage signal, together with the graded shunt that acts on

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the BMS domain when the statistic rises persistently towards 1.

For a lithium-ion cell: in a healthy cell, small voltage fluctuations within each cycle return to the baseline quickly. As the cell approaches its knee point, whether from lithium plating, loss of active material or loss of lithium inventory [4], the same small fluctuations take longer to settle. The lag-1 autocorrelation rises.

- **Healthy cell:** voltage residual returns to baseline quickly. Lag-1 autocorrelation W : low.
- **Cell approaching knee point:** voltage residual settles more slowly, before any capacity threshold is crossed. Lag-1 autocorrelation W : rising persistently towards 1.

4 The Assumed Raw Readings

This note does not know which readings any particular BMS stores. To make the requirement concrete, the readings below are assumed and named by the author.

Name	What it is (assumed)	Rate needed	Used for
V_CELL	Raw cell voltage, as a continuous time series within each cycle, before any averaging	1 Hz or faster	The signal whose recovery speed is watched
I_PACK	Pack current	1 Hz or faster	To separate voltage response from load variation
T_CELL	Cell temperature	1 Hz or faster	To separate thermal drift from chemical drift
SOC	State of charge as reported by the BMS	Per reading	To compare like cycles
CYCLE	Cycle counter or label	Per cycle	To align the analysis
TIME	Exact time stamp for every V_CELL reading	With every V_CELL	All timing

Raw readings are essential. A BMS that stores only a smoothed or cycle-averaged voltage hides the within-cycle variation the method reads.

5 The Calculation

Step 1. Within each cycle, take V_CELL as recorded at the same SOC window. Remove the slow within-cycle trend using only past and present values. The residual is what remains.

Step 2. At the end of each cycle, compute the lag-1 autocorrelation of the residual over a rolling window of the most recent cycles. This is the warning number W .

Step 3. Raise a level only when W stays above its alarm line for several consecutive cycles. A single high value may be noise.

Step 4. As a second channel, compute the variance of the residual over the same window. Both rising together give a stronger signal [1].

No training and no reference history are needed. W is computed from the cell's own cycles. It works from the first cycles of any run.

6 The Shunt: A Graded Response Acting Only on the BMS Domain

The shunt is the core of the invention. When W rises persistently towards 1, a graded response acts on the entities of the closed BMS domain: the charger controller, the thermal management system, the cell balancer and the BMS alert system. The shunt never reaches beyond the battery pack.

- **Level 1 (W rises above the first alarm line):** flag the affected cell. Log the warning number with a time stamp.
- **Level 2 (W rises above the second alarm line):** reduce the charge rate for that cell. Alert the fleet management system or the driver.
- **Level 3 (W rises persistently towards 1):** pause charging before the next cycle. Hold until the operator or the service system inspects and decides.

The shunt changes the state of the BMS. It acts early, while the cell voltage is still within its normal operating range, so that a correction is gentle and reversible.

7 The Data a First Test Would Need

- V_CELL as raw voltage within each cycle at 1 Hz or faster, with I_PACK, T_CELL, SOC, CYCLE and TIME, from a range of cells including some that reached the knee point.
- A record of which cycles the BMS flagged as anomalous, so that the warning can be compared with the BMS's own record.
- A statement of whether the stored values are raw or averaged.

8 Scope and Next Step

This is a concept note. No battery data have been analysed. The slowing of voltage-residual recovery is a hypothesis for an early sign of approach to the knee point; a controlled study on real BMS logs is needed to test it. Temperature, driving-cycle variation and cell chemistry all affect the voltage signal, and each may need its own correction. The next step is to run the fixed calculation on a BMS operator's own raw voltage records and to compare the moment the warning number rises persistently with the moment the BMS flags the cell or the capacity crosses a threshold.

References

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