EFPTM vs. Traditional Methods for Defect Detection

White Paper - Tab-Welding Quality Control

Core message

Tab-weld quality of a battery cell is an internal connection problem: many anode and cathode sheets are welded to the current-collector tab inside the cell, and the resulting quality is better described as a continuum than a binary perfect/bad split. This is typically detected accurately only by CT-scans, which are suitable for sample testing only in high-volume manufactruing. OCV, ACIR and DCIR compress that structure into single numbers. CeLLife's EFPTM preserves richer electrical behavior and can serve as the primary inline electrical test. At the same time, familiar outputs such as OCV, ACIR and DCIR can also be extracted from the EFPTM measurement.

Why EFPTM is different

OCV reflects only cell voltage state. ACIR gives one resistance value under one measurement condition. Both are useful baselines in manufacturing, but both compress the cell into a one scalar number. CeLLife's Electrical Fingerprint (EFPTM) retains a full-spectrum impedance in 5 seconds over the whole relevant frequency region. That richer electrical description makes it possible to build indicators that are more sensitive to internal current-collection and weld-quality variation than OCV, ACIR or DCIR alone.

Comprehensive EFPTM data enables analysis of deep multi-characteristic phenomena and combining this data into informative-rich indicators describing electrical behavior not just single-frequency data points. Because it is the richer measurement, EFPTM can also replace OCV and ACIR (and DCIR) rather than only supplement them [1-2].

Parameter	What it tells you	Best role in cell QC	Main limit for tab-weld discrimination
OCV	Voltage state, polarity, gross consistency	Sanity check, balancing context	No sensitivity to internal weld-quality variation
ACIR	One resistance value at one measurement condition	Legacy fast baseline if retained	Still a single scalar; loses defect-specific structure
EFPTM defect indicator	A derived feature selected from the EFPTM response	Primary inline electrical test; can replace OCV/ACIR/DCIR	Complex data, needs careful feature selection and know-how
CT reference	Physical ground truth on sampled cells	Labeling, failure analysis, process validation	Too slow and costly for every-cell inline testing

Illustrative CT-referenced example

In the presented case, the CT-referenced set contained 100 good cells and 100 cells with tab-weld issues spanning multiple severities. ACIR shows heavy overlap and reached 38% mislabeling at its optimal threshold. A single EFPTM defect indicator reduces mislabeling to 14%. Combining ACIR and single EFPTM defect indicator with a simple linear boundary brings the rate to 12%, and with a trained ML-based nonlinear boundaries reach 11% - only by using a single EFPTM indicator and traditional ACIR. These values are case-specific, but progression is the key point: better parameters first, then more dimensions, then more flexible boundaries.

How to interpret the example

CT-scans were reviewed manually by a few individual human analysts, so reference-label noise is possible and probable. That matters because weld quality is better described as a continuous distribution than a strict binary good/bad split. The durable result is therefore the trend: richer EFPTM information separates the population better than scalar OCV or ACIR.

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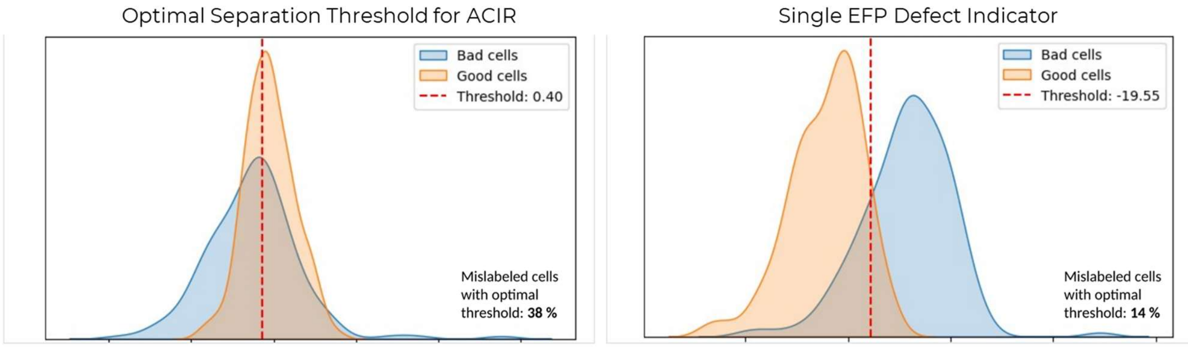
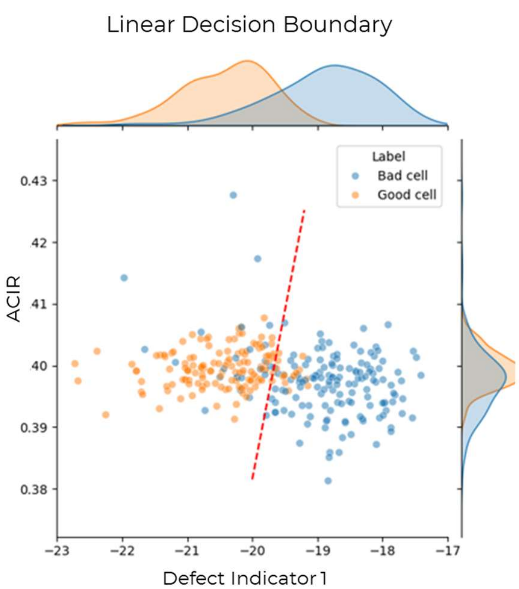
Results Summary

The first step is not "use AI"; it is "choose informative-rich and relevant variable(s) for the problem." For tab welding and other mechanical issues, that usually means looking toward the high-frequency cell behavior, where current-path and contact disturbances are most visible. A single EFP™ defect indicator can therefore outperform traditional parameters simply because it is selected carefully from a more relevant part of the spectrum and carries more information than just a one scalar data point.

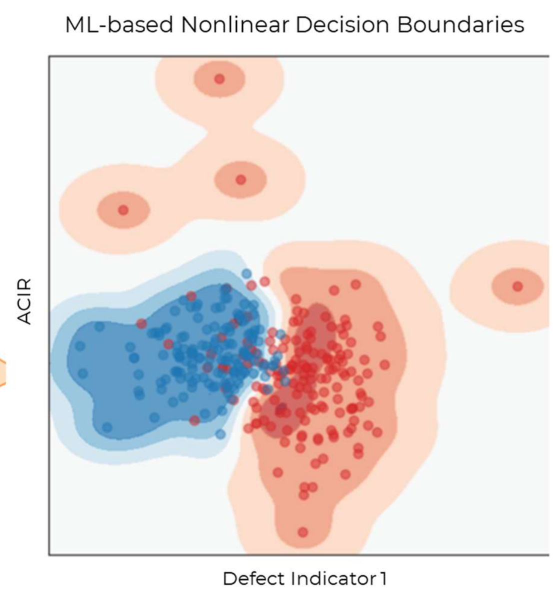


CT-referenced example with 100 good and defected cells: ACIR shows heavy overlap, while single EFP defect indicator separates the classes more clearly.

Once one strong indicator is found, the next step is typically to add a second variable and ask whether a simple boundary is already enough. Even a linear boundary can exploit complementary information that is weak on its own but useful in combination. When that still leaves structured overlap, ML learns the non-linear boundaries or clustered regions that manual thresholds cannot express.



ACIR and single EFP defect indicator. A simple linear boundary improves separation over either variable alone (12 % mislabeling).



Nonlinear ML boundaries. Model learns decision boundaries from reference data, enabling nonlinear boundaries (11 % mislabeling)

The point of the nonlinear step is not only a small extra gain in one data set. The bigger value is structural: ML can represent the real geometry of defect classes, capture variable interactions, and reduce the burden of hand-maintained threshold logic.

When information-rich EFP™ indicators are added more, the problem becomes truly multidimensional. That matters because tab-weld quality is rarely one single failure mode. Different weld states, contact conditions, material lots, and process deviations can create overlapping signatures that only separate cleanly when several informative-rich features and indicators are considered together.

Illustrative progression in this laboratory case

Method	Illustrative mislabel rate	What it shows
ACIR only	38%	Heavy overlap; weak 1D separation
Single EFP™ defect indicator	14%	One informative indicator outperforms ACIR
ACIR + EFP™ defect indicator, linear boundary	12%	A second informative dimension improves separation
Nonlinear ML-based boundary	11%	Learned boundaries capture interactions beyond straight lines

How CT and EFP™ should work together

CT-scans should be the reference, not the line test. CT can reveal internal weld geometry and related manufacturing defects, but it is comparatively slow and expensive and therefore best used for sample-based truth data, validation, and failure analysis [3]. EFP™ is the scalable layer: it turns that defect knowledge into a production-compatible electrical test for every cell and can replace OCV/ACIR/DCIR as the main inline electrical measurement.

- Use CT-scanned cells as training data on quality bands and to confirm physical failure modes.
- Select the EFP™ indicators that separate quality bands most clearly.
- Train models by certain cell type and defect mode to achieve the most reliable results.
- Use EFP™ as inline electrical screen; retain separate OCV/ACIR/DCIR reporting only if needed.

Measurement discipline required - or compensation

Keep temperature, charge state/rest condition, probe force, and fixturing stable – or build condition compensation model for results. Segment models by chemistry, design, and weld recipe for the most reliable results. At first, expect soft class boundaries because weld quality varies continuously and the CT reference may include human interpretation error – use CT to collect more training/validation data about unclear cells. ML/AI based solutions will improve with accumulating data, this will reduce need for CT-scanning.

Conclusion

For tab-weld quality control, the main advantage of EFP™ is not simply that it measures more data fast. It can replace conventional OCV, ACIR and DCIR checks while preserving the richer electrical structure needed to resolve internal weld-quality variation – and other quality problems - across a continuous quality distribution. That is why EFP™ parameters can materially outperform traditional scalar checks in CT-referenced manufacturing screening.

Selected sources

[1] Hioki, BATTERY HiTESTER BT3562A - AC-IR and OCV production testing page, accessed March 2026.

[2] Osswald, P. J. et al., "Current density distribution in cylindrical Li-Ion cells during impedance measurements," Journal of Power Sources 314 (2016) 93-101.

[3] Wu, Y. et al., "Analysis of Manufacturing-Induced Defects and Structural Deformations in Lithium-Ion Batteries Using Computed Tomography," Energies 11 (2018) 925.