Understanding Battery Aging with Knowledge Guided AI

An electric vehicle can report how much charge remains in its battery. Assessing how the battery is aging is harder. A *state of health* estimate offers a useful measure of its condition, but it does not necessarily explain what is changing inside the cell. For engineers responsible for monitoring performance and planning maintenance, that explanation matters as much as the number.

Modern AI has largely been built around cloud infrastructure, where large datasets and powerful computers are concentrated. As connected devices and sensors generate more data, some processing is moving closer to its source. In a vehicle, local processing can support timely decisions when a round trip to a remote server would be too slow or connectivity is unreliable. It can also limit the transfer of sensitive data.

This shift brings its own engineering trade-offs. A model must remain accurate while meeting limits on response time, memory and energy use. Hardware varies across devices, and performance measured in a laboratory may change after deployment. The gap between a model that works in an experiment and a system that works reliably on physical hardware is a central challenge for edge and embedded AI.

Battery monitoring offers a concrete case in this wider edge AI landscape. The study examined here asks: **can AI describe battery aging in a way that is both understandable and consistent with electrochemical evidence?** The proposed framework combines electrical measurements, a large language model and a structured body of domain knowledge to produce explanations that can be checked against the data [1].



Figure 1. Conceptual division of battery diagnostics between onboard processing and local or cloud-assisted reasoning.

What a battery's electrical response can reveal

Electrochemical impedance spectroscopy, usually shortened to **EIS**, measures how a battery responds to electrical signals across a range of frequencies. Different regions of the resulting spectrum can provide clues about processes such as resistance at the battery's interfaces, charge transfer and diffusion. EIS is a valuable tool for investigating battery materials and their changing condition, although translating a spectrum into a diagnosis requires care [2].

Previous research has used impedance measurements and machine learning to identify battery degradation patterns [3]. Many diagnostic methods, however, concentrate on predicting a health value. This study asks an additional question: **what observed changes support a particular explanation of aging?**

To make the measurements manageable, the framework reduces each EIS spectrum to five characteristic points. Together, they summarize features from the high, middle and low frequency regions. The system then follows those points over successive measurements, recording how far and in which direction they move. This preserves information about the battery's evolution while producing a much smaller representation than the original spectra [1].

The measurements are converted into a structured description that a large language model can read. It includes the selected points, derived indicators and trends over time. The model uses this information to assess the aging pattern and propose possible mechanisms behind it.

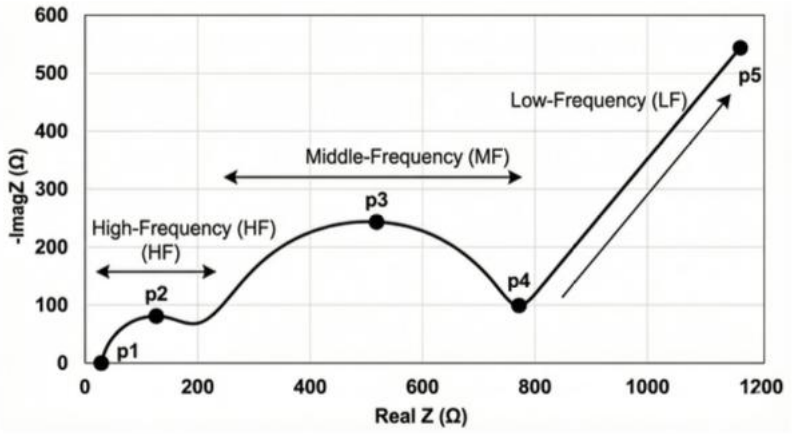

Figure 2. Five characteristic points selected from an EIS spectrum. Source: [1].

Giving the explanation a scientific check

A language model can express complex findings in accessible prose. It can also produce a statement that sounds plausible without being supported by the measurements. In a scientific diagnosis, clear writing is useful only if the underlying claim can be traced back to evidence.

The proposed framework addresses this with an **electrochemical knowledge graph**: a structured set of relationships between measured indicators, electrochemical effects and possible degradation mechanisms. A rule layer checks the model's explanation against those relationships. For example, if an explanation invokes a diffusion related process, the system examines whether the relevant low frequency measurements are reliable enough to support it [1].

When a claim fails the check, the system provides feedback and asks the model to revise its answer. If it cannot produce an acceptable explanation after the permitted revisions, it returns a more conservative account that states the remaining uncertainty. The aim is not to make the language model an independent electrochemistry expert. It is to make its reasoning more accountable to the observed data.

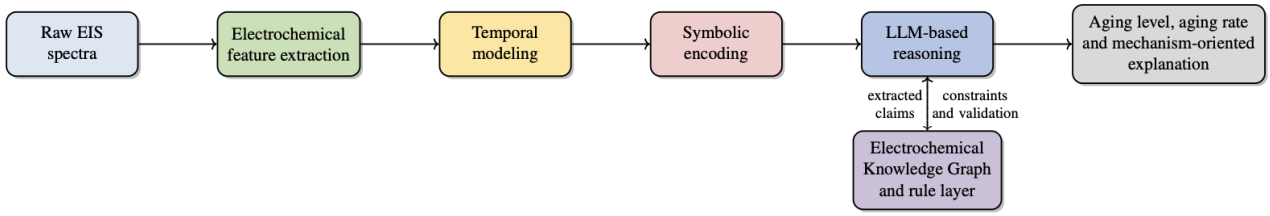

Figure 3. Knowledge-guided architecture for battery aging analysis. Source: [1].

What the tests showed

The framework was evaluated using a public dataset containing EIS measurements taken as lithium-ion cells aged. The comparison included numerical health estimation methods and two other ways of generating explanations: a language model without the knowledge checks, and fixed explanations built from rules [1].

The contrast with the unconstrained language model is substantial. The share of explanations containing at least one degradation mechanism claim unsupported by the observed trends fell from **31.6% to 18.2%**. Explanations consistent with the electrochemical rules rose from **68.7% to 91.5%**. The knowledge guided approach also covered more of the relevant mechanisms than the fixed rule templates, while remaining close to them in rule consistency [1].

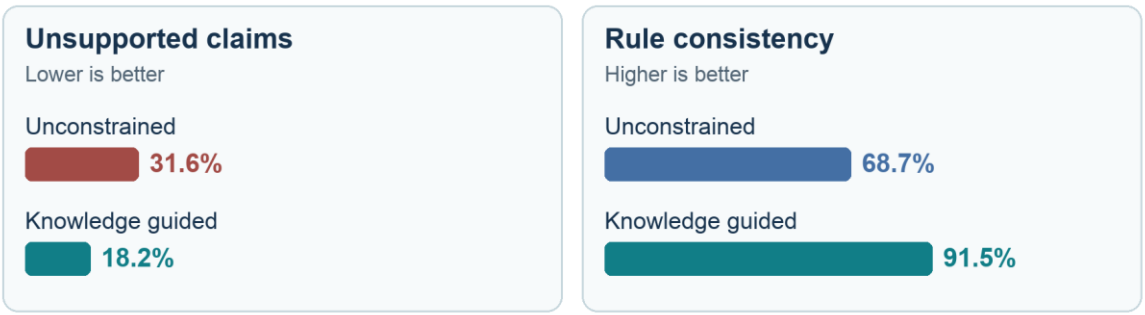

Figure 4. Explanation quality on the test set. Values reported in [1].

There is an important qualification. In this study, a proposed degradation mechanism is an **evidence-based hypothesis**, not a direct observation of the physical process inside the cell. The checks reduce unsupported claims, but they do not eliminate them. A smaller expert review, covering 24 explanations from four cells, provided an additional assessment of whether the proposed mechanisms matched the observed indicators [1].

The framework's numerical health estimate was competitive with simpler feature-based approaches, although a temporal Transformer achieved a lower prediction error in the reported comparison. The distinctive contribution of the framework is therefore the explanation alongside the estimate: it shows which trends led to a diagnostic hypothesis and applies a check before presenting it [1].

From research framework to onboard diagnostics

The study also considers how this approach might fit into a battery management system. Extracting the EIS features and encoding their trends produces a compact description of approximately **350 bytes per observation window**. In the proposed architecture, these numerical steps could run on board, while the explanation stage could use a combination of vehicle and cloud computing or suitable local hardware [1]. This division of work reflects the cloud–edge continuum: processing can be placed where response time, connectivity and available computing resources allow it.

This is a proposed deployment architecture. The reported experiments use a public dataset; they do not establish that the complete system has been validated in a working vehicle. This distinction reflects the deployment gap: a method tested with stored measurements may behave differently on physical hardware, under real operating conditions and with variable measurement quality [1].

The paper identifies low frequency measurement noise as a particular limitation. If the initial indicators are unreliable, the knowledge graph cannot fully correct the resulting interpretation. Future work will need to test the approach across more battery types and datasets and improve the extraction of features from noisy measurements [1].

For now, the study points toward a useful direction for battery monitoring. A health score can tell us that a cell is changing. A carefully checked explanation can help show **which measurements prompted that assessment, what might be happening and where the evidence remains uncertain**.

Illustrative prompt example

This example illustrates the structured input described in the study.

```
messages:
- role: system
 content: |
 Expert in Li-ion EIS diagnostics.
 Use only provided data.
 Do not introduce new quantities.
 Output strictly in the YAML schema.


- role: user
 content: |
 Diagnose aging from EIS summary.
 cell: C17
 cycles: [420, 460]
 P: [[32.4,0.8],
 [45.1,18.7],
 [76.6,41.8],
```

```
[92.7,33.5],
[118.3,55.9]]
# (Re, -Im) mOhm
ind:
HF_int: 32.4
HF_arc: 12.7
MID_Span: 47.6
LF_ext: 38.2
LF_slope: 0.87
dlt: # Euclidean drift magnitude (unsigned)
HF_int: 3.1
HF_arc: 8.9
MID_Span: 21.4
LF_ext: 4.6
LF_slope: 1.2
trd: # Direction extracted from trajectory
HF_int: stable
HF_arc: inc
MID_Span: inc
LF_ext: sl_inc
LF_slope: stable
lf_rel: moderate
soh_ref: 87.3
Tasks:
- estimate aging level
(qualitative, SOH range)
- assess degradation rate
- explain mechanisms linked
to indicators
- if lf_rel != high,
avoid diffusion-only claims
Output (YAML):
aging_assessment:
mechanism_interpretation:
consistency_notes:
```

References

[1] F. La Rosa, P. Dell'Acqua, L. Carnevale and M. Villari, "Knowledge-Guided LLMs for Aging Assessment and Interpretation of Lithium-Ion Batteries from Electrochemical Impedance Spectroscopy," manuscript supplied for this newsletter.

[2] M. Gaberšček, "Understanding Li-based battery materials via electrochemical impedance spectroscopy," *Nature Communications*, vol. 12, article 6513, 2021.

[3] Y. Zhang, Q. Tang, Y. Zhang, J. Wang, U. Stimming and A. A. Lee, "Identifying degradation patterns of lithium-ion batteries from impedance spectroscopy using machine learning," *Nature Communications*, vol. 11, article 1706, 2020.