

SEPTEMBER 03TH 2024

Perspectives on Commercial Sodium-Ion Batteries

Dr. Minglong He, ABB Switzerland ECCE Europe 2024





- 1. Landscape of commercial sodium-ion battery development
- 2. ABB's engagement and position
- 3. Results of commercial sodium-ion battery assessments
- 4. Summary and perspectives

Motivation of Sodium-ion Battery

Sodium resource ~ 1000 times of Li resource

Sodium Battery from Science Fiction in 1870



Jules Verne (1828 – 1905)¹



Twenty Thousand Leagues Under the Sea (1869 – 1870)²

Captain Nemo: I'll mention that sodium batteries have been found to generate the greater energy, and their electro-motor strength is twice that of zinc batteries. Only the sodium is consumed, and the sea itself gives me that.

Trend of sodium-ion technology



1 https://en.wikipedia.org/wiki/Jules_Verne

Slide 3 2 https://www.storytel.com/in/en/books/20-000-leagues-under-the-sea-185335

3 Chayambuka, K., Mulder, G., Danilov, D. L., Notten, P. H. L., Adv. Energy Mater. 2018, 8, 1800079. https://doi.org/10.1002/aenm.201800079

Sodium-ion Cell Chemistry



Cathode:

- Layered oxides (example: NaFe_{0.33}Ni_{0.33}Mn_{0.33}O₂)
- Polyanionic compounds (example: Na-FePO₄)
- Prusisan blue analogues (example: Na_xMn_yFe(CN)₆·nH₂O)

Anode:

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- Hard carbon/soft carbon
- Metal oxide (example: LTO)
- Prusisan blue analogues (example: Na_xMn_yMn(CN)₆·nH₂O)
- Metal alloy (example: Sn)



Representative Sodium-ion Startups and Companies



Sodium-ion Batteries Become Important Alternatives to Lithium-ion Batteries

BYD breaks ground on new 30GWh sodium-ion battery facility in China

BYD is building the new sodium-ion battery facility in Xuzhou with an investment of nearly 10bn yuan (\$1.4bn).



Sineng Electric launches world's largest sodium-ion battery storage project

Sineng Electric's 50 MW/100 MWh sodium-ion battery energy storage system (BESS) project in China's Hubei province is the first phase of a larger plan that will eventually reach 100 MW/200 MWh. The initial capacity has already been connected to the grid and can power around 12,000 households for an entire day.

AUGUST 8, 2024 CARRIE HAMPEL



Natron Energy starts manufacturing '50,000+ cycle-life' sodium-ion batteries at Michigan factory

By <u>Cameron Murray</u> April 30, 2024

Tiamat to build a 5 GWh factory for sodium-ion batteries in France

The French company Tiamat Energy is planning a factory for sodium-ion battery cells with an annual capacity of 5 GWh in northern France - and is receiving financial support from Stellantis, among others. (UPDATE BELOW)

First sodium-ion battery EVs go into serial production in China

The first electric cars with sodium-ion batteries have gone into production in China. The two small electric car models are being manufactured by Yiwei and JMEV.



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- https://www.electrive.com/2024/01/12/tiamat-to-build-a-5-gwh-factory-for-na-ion-batteries-in-france/
 https://www.energy-storage.news/natron-energy-starts-manufacturing-50000-cycle-life-sodium-ion-batteries-at-michigan-factory/
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.<u>https://www.pv-magazine.com/2024/08/08/sineng-electric-launches-worlds-largest-sodium-ion-battery-storage-project/</u>

ABB's Engagement and Position

Energy Storage Applications

Stationary



Transportation

ABB offers solutions in most of the given examples

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Remark: Typical values and some examples for the purpose of illustration are given. In reality, the values can vary considerably, depending on the specific cases. ABB

ABB's Positioning on Storage

- ABB does not manufacture battery cells
- ABB selects the optimal technology for the application (examples below)
- ABB acts as product supplier and system integrator



ABB's Engagement – Sodium-ion Battery Technology

ABB selects the optimal technology for the application

Natron Prussian blue-based Na-ion battery



Journal of Power Sources Volume 548, 15 November 2022, 232036

Assessment of the first commercial Prussian blue based sodium-ion battery

<u>Minglong He ^a ∧ ⊠</u>, <u>Roy Davis ^b</u>, <u>Daniel Chartouni ^a</u>, <u>Mark Johnson ^b</u>, <u>Markus Abplanalp ^a</u>, Pirmin Troendle ^a, Ralf-Patrick Suetterlin ^a





Tiamat NVPF/HC-based Na-ion battery



Journal of Power Sources Volume 588, 30 December 2023, 233741

High power NVPF/HC-based sodium-ion batteries

Minglong He^a $\stackrel{\circ}{\sim}$ $\stackrel{\boxtimes}{\boxtimes}$, Asmae EL. Mejdoubi^b, Daniel Chartouni^a, Mathieu Morcrette^b, Pirmin Troendle^a, Roberto Castiglioni^a





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https://doi.org/10.1016/j.jpowsour.2022.232036
 https://doi.org/10.1016/j.jpowsour.2023.233741

Results of commercial sodium-ion battery assessments



Fundamentals of Natron Na-ion battery

Battery materials and electrochemistry

Electrode materials



Cathode

Na_xMn_yFe(CN)₆·nH₂O (Sodium manganese-iron hexacyanoferrate) 200-500 nm primary particles 10-20 µm secondary particles

Cell voltage and capacity



- Cathode specific capacity: 67 mAh/g
- Cathode average potential: 0.9V vs. SHE

- Anode specific capacity: 68mAh/g
- Anode average potential: -0.7V vs. SHE



Anode

Na_xMn_yMn(CN)₆·nH₂O (Sodium manganese hexacyanomanganate) 2-3 µm particles



Natron Prussian Blue-based Sodium-ion Battery Cell

Basic cell information

Cell information



- Cell capacity: 4.6 Ah
- Specific energy of 23 Wh/kg

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DC internal resistance - DCIR



- Cell internal resistance of 1.4 mOhm (10ms, 50% SOC)
- Rough estimation of the short circuit current on cell level at 50% SOC is 1086 A derived by applying Ohm's Law (the OCV at 50% SOC is 1.52 V).

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Natron Prussian Blue-based Sodium-ion Battery Cell

Rated performance

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Rated Charge performance

1.9 1.8 Cell voltage (V) 1.7 1.6 1.5 1.4 2C charge -1¢ charge -4C charge 1.3 8C charge -10C charge 1.2 0% 80% 90% 100% 10% 20% 70% 30% 40% 50% 60% State of Charge (SOC %)

Charged from 0% SOC to 80% SOC in < 5 minutes and to 99% SOC in < 10 minutes.

Rated discharge performance



• 88% discharge capacity at a 10C rate in comparison to 1C discharge.

• Natron: a maximum continuous charge C rate of 17C and a maximum continues discharge C rate of 54C are allowed at the cell level.

Natron Prussian Blue-based Sodium-ion Battery Cell

Cycle life performance

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Ageing tests performed in ABB's battery lab

• Capacity loss of about 2% after 4200 cycles with 10C charge and 10C discharge

• Cycle life of >40,000 cycles is estimated if a linear extrapolation is applied

Ageing tests performed in Natron's battery lab



- Cycle life of >40,000 cycles to 80% initial capacity
- Cycle life >90,000 cycles to 60% initial capacity

Natron Prussian Blue-based Sodium-ion Battery Module

Battery module performance

Battery module information



Capacity of 4.6 Ah, energy of 0.22 kWh, and energy density of 10.3 Wh/kg

• Voltage range of 32 V–58 V, an average voltage of 50.3 V at 50% SOC.

Battery module rated charge performance



- A movimum temperature increase of 8 °C was detected with 200
- A maximum temperature increase of 8 °C was detected with 20C charge

Natron Prussian Blue-based Sodium-ion Battery Module

Battery module performance

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Battery module rated charge performance

The module (32 cells) can be charged from 0% SOC to 80% SOC in <5 min and to 99% SOC in <10 min.

Module constant power dischage performance



- Up to 6 kW of battery backup for 1 min discharges and up to 1 kW for 12 min, with end of discharge voltage of 32 V
- A discharge power of 4 kW for 2 min (350 W/Liter for those 2 min)



Safety Evaluation

Abuse tests based on UL9540A methods

Short circuit test



- The current at the initial short circuit was about 796 A
- No venting and no thermal runway were observed
- A minor extent of cell swelling was observed in the center

Overcharge test



- Constant current, voltage from 1.73 V to 26 V at a rate of 1 V/min
- At 26 minutes, flame was observed at voltage of 26 V, temperature increase to 150-200 °C
- When the power supply turned off, the flames self-extinguished.

Nail penetration test



- 8 mm diameter, 125 mm long nail used
- The nail increased in temperature slightly (ca. 2°C)
- No venting and no thermal runway



Natron Battery Shooting Test





Comparison to Other Energy Storage Devices

- Performance characteristics between batteries and supercapacitors in terms of power, energy density, and cycle life ٠
- The Prussian Blue-based sodium-ion technology could be applicable for high-power applications (e.g., uninterruptible power supply), providing ٠ alternatives to the existing battery solutions.

A rated power density of up to 1250 W/kg

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ABB Engagement - Sodium-ion Battery Technology odules Rectifier Natron Energy Natron Energy, California, USA Battery Modules TECHNOLOGY VENTURES HDR Sodium Ion/Prussian Blue -BME2500/220NAION48 In 2020, Natron Energy announced they have ower B raised \$35 million in Series D funding. ABB Technology Ventures, NanoDimension Capital and Volta Energy Technologies co-led the round, with existing investors Chevron, Khosla

Edge Datacenter Cabinet (ABB Power Conversion division*)

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AC Input(s)

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Space

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continuing

their

Ventures

and

participation in funding.

Prelude



Cable Management

Supplemental Batteries

Summary and Perspectives

Summary and Perspectives

- Energy density: The state-of-the-art Na-ion batteries typically have energy densities of 20-160 Wh/kg, which is targeted to reach more than 200 Wh/kg for the next-generation cells. Na-ion batteries can achieve a comparable energy density to LFP batteries.
- **Power density:** The layered oxide-based sodium-ion batteries have a comparable power density to lithium-ion batteries, while PBA and polyanionic based sodium-ion batteries exhibit attractive performance features of ultra-high-power density.
- Cycle life: PBA/PBA sodium-ion batteries from Natron Energy have the highest cycle number (up to 40'000 cycles) among all batteries. The other Na-ion batteries have cycle life of 1000-4500 cycles.
- Safety: Different sodium-ion batteries have shown superior thermal stability and abuse tolerance in comparison to LFP and NMC batteries.
- **Maturity:** Multiple prototypes of sodium-ion cells and modules have been developed and deliver promising results. The sodium-ion technology starts ramping up mass production.
- R&D focus: The main R&D direction for sodium-ion battery technology lies in improving energy density (target of 200 Wh/kg) and cycle life.
- **Cost:** The frequently discussed cost advantage of Na-ion batteries highly depends on the prices of Li-ion raw materials. Sodium-ion batteries become cost-competitive in the case of high prices of lithium, cobalt, and nickel.





Electrochemical Impedance Spectroscopy and Prognostics in Battery Systems

Prasanth Venugopal, Ning Zhansheng, Reza Azizighalehsari, Gert Rietveld & Thiago Batista Soeiro













mmmm



1. Introduction to Battery Degradation

2. Introduction to EIS (Electrochemical Impedance Spectroscopy)

3. EIS and its connection to EEM

4. Factors influencing good EIS

5. Capacity Predictions using ML/AI Tools



GLOBAL MARKETS AND BATTERIES GROWTH



EV: 35% year-on-year increase 23/22







Global cumulative energy storage installations, 2015-30



Energy Storage Market Set to Grow 20x by 2030

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DEGRADATION MODES IN BATTERIES







SOC AND SOH ESTIMATION TECHNIQUES









- Electrochemical system is probed with an ac current (Galvanostatic), the voltage response recorded, and impedance interpreted
- ✓ For other systems, the probing technique can be **Potentiostatic** (high impedance systems)





ELECTROCHEMICAL IMPEDANCE SPECTROSCOPY



Features:

- Small signal injection \rightarrow quasi-LTI system and models battery dynamics
- System in thermodynamic equilibrium (or 'steady state')
- Measurement is small perturbation (approximately linear)
- Different processes have different time constants
- Large frequency range, µHz to GHz (and up)







Disadvantages:

- Expensive equipment esp. with high accuracy
- Low frequencies are difficult to measure







IMPACT OF SIGNAL AMPLITUDE





- Injected current amplitude directly influences impedance spectra quality, notably at low frequencies.
- Small amplitude preserves battery state, maintains linearity, reflects actual operating conditions, and minimizes system perturbation for accurate interpretation.
- Balance needed between linearity/stability and sensitivity for precise impedance analysis.
- Selection based on the battery's characteristics and acceptable accuracy range in EIS spectra.

S. Azizighalehsari, Z. Ning, B. Breazu, P. Venugopal, G. Rietveld and T. B. Soeiro, "Battery Dynamics Exploration: Insights and Implications of Relaxation Time in Electrochemical Impedance Spectroscopy," 2023 IEEE 8th Southern Power Electronics Conference and 17th Brazilian Power Electronics Conference (SPEC/COBEP), Florianopolis, Brazil, 2023, pp. 1-6, doi: 10.1109/SPEC56436.2023.10407778.











- Adequate rest period is crucial for accurate representation of electrochemical behavior.
- Allows dissipation of transient effects, ensuring impedance measurements reflect actual cell behavior.



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S. Azizighalehsari, Z. Ning, B. Breazu, P. Venugopal, G. Rietveld and T. B. Soeiro, "Battery Dynamics Exploration: Insights and Implications of Relaxation Time in Electrochemical Impedance Spectroscopy," 2023 IEEE 8th Southern Power Electronics Conference and 17th Brazilian Power Electronics Conference (SPEC/COBEP), Florianopolis, Brazil, 2023, pp. 1-6, doi: 10.1109/SPEC56436.2023.10407778.













- 1) f > 1 kHz and τ < 10ms: Contact resistance corresponding to particle-particle or particle current.
- 2) 1 kHz < f < 100 Hz and 1 ms < τ < 10 ms: Transport of Liions in the Solid-Electrolyte Interface (SEI).
- 3) 10 mHz < f < 100 Hz and 10 ms < τ < 10 s: Dual electroderelated charge transfer resulting in two or more peaks.
- 4) f < 100 mHz and τ > 10s: Diffusion related slow electrochemical process
- Ideal ECM must model the electrode dependent, battery dynamics (non-linearity) completely
 - \rightarrow Low frequency diffusion process
 - \rightarrow Charge transfer electrochemistry
 - \rightarrow Double layer capacitance effect (voltage dependent)
- The high frequency region is often neglected for individual cells (but has significance for modules and packs, online EIS)

S. Azizighalehsari, E. A. Boj, P. Venugopal, T. B. Soeiro and G. Rietveld, "A Distribution of Relaxation Time Approach on Equivalent Circuit Model Parameterization to Analyse Li-ion Battery Degradation," in *IEEE Transactions on Industry Applications*, doi: 10.1109/TIA.2024.3430268.











ECM EVOLUTION FOR BATTERY MODELS







EIS FOR BATTERY CAPACITY ESTIMATION USING ML/AI





Input: Impedance

Output: Capacity

Ning, Zhansheng, et al. "Computation-light AI models for Robust Battery Capacity Estimation based on Electrochemical Impedance Spectroscopy." IEEE Transactions on Transportation Electrification (2024).











EIS FOR BATTERY CAPACITY ESTIMATION





Two approaches for evaluating the characteristics of the battery system



Evaluation results based on Kramers-Kronig relations

















CORRELATION ANALYSIS FOR BATTERY CELLS



Correlation Analysis for All Cells



Pearson correlation coefficient (p)



 ρ of imaginary-part of Impedance (Z_{Im})



• The **imaginary** part of impedance, the **CPE**, and the **Warburg** element have a high correlation with the battery capacity for all cells











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EIS FOR BATTERY CAPACITY ESTIMATION



Feature consistency coefficient (FC)





Feature consistency analysis of parameters of ECM

The pre-processed Z_{Im} at a frequency of **2 Hz (Z_{Im} (2Hz))**, and the **CPEQ** of ECM have the highest feature consistency

POWER ELECTRONICS











• Results, Accuracy & Time Complexity





All-EIS-based CNN: 37.85 ms

Partial-EIS-based CNN: 21.48 ms

Robustness Analysis

- RMSE: Worst Case: 2.5%
- RMSE: Best Case: 1.4%











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Al-Powered Data Analysis for Battery Aging and Safety Assessment

ECCE Europe 2024

9/3/2024 Dr.-Ing. Weihan Li

Center for Ageing, Reliability and Lifetime Prediction of Electrochemical and Power Electronic Systems (CARL) Center for Ageing, Reliability and Lifetime Prediction of Electrochemical and Power Electronic Systems



Center for Ageing, Reliability and Lifetime Prediction for Electrochemical and Electronics systems – Supporting battery applications and battery production

- 2150m² office area
- 2750m² laboratory area
- >150 researchers
- 120 Mio. € investment



- >4000 battery testing channels
- Environmental stress lab
- Chemistry lab
- Clean room & Drying room
- CT & Microscopy



Mechanical & electrical workshops





Circle of Innovation



Center for Ageing, Reliability and Lifetime Prediction of Electrochemical and Power CARL Electrochemical and Electronic Systems



3

Machine learning for safe, efficient and sustainable battery use



4

CARRL Center for Ageing, Reliability and Lifetime Prediction of Electrochemical and Power Electronic Systems



State-of-the-art experimental parameter measurements



Li W, et al., Energy Storage Materials, 2022 (44): 557-570.



State-of-the-art experimental parameter measurements



CARL Center for Ageing, Reliability and Lifetime Prediction of Electronic Systems

Results: Experimental vs. Data-driven



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Online aging diagnosis by integrating physics and AI

- Data
 - Low-dynamic profile
 - High-dynamic profile
- Battery model
 - Impedance-based model
 - OCV model
- Artificial Intelligence
 - Cuckoo search algorithm



Li W, et al. 2022, Energy Storage Materials, 53, 391-403.



Combining the impedance-based model and OCV reconstruction model

 U_{max}

 U_{min}

- Equivalent-circuit model
 - Ohmic resistance
 - Charge transfer
 - Diffusion
- OCV reconstruction model
 - Electrode OCP
 - OCV balancing parameters
 - Cut-off voltages: U_{max}, U_{min}





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Online OCV reconstruction

- OCV reconstruction
 - Benchmark: qOCV test
- Incremental capacity analysis
 - Qualitative evaluation of the degradation modes



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Online aging mode identification



Identification results of stoichiometric parameters and degradation modes

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Overview of the variables in field data

NameDescriptionValue rangeSingle valuesSOHstate of health at readout $[0, 100]$ (%)SOCstate of charge at readout $[0, 100]$ (%)energy_throughputtotal battery energy throughput until readout $[0, 8,000]$ (kWh)voltagebattery voltage at readout $[0, 70]$ (V)currentbattery current at readout $[-1,500, 1,500]$ (A)temperaturebattery temperature at readout $[-126, 126]$ (°C)Histogram valuestime spent in SOC range $[0, 10, 20,, 100]$ (%) $[0, 2^{32} - 1]$ (s)time_temperature_x, x \in $[1, 6]$ time spent in temperature range $[0, 0, 20,, >70]$ (°C) $[0, 2^{32} - 1]$ (s)(dis)charge_temperature_x, x \in [1,7]number of DODs in range $[0, 1.1, 2.2,, >9.9]$ (Ah) $[0, 2^{32} - 1]$ (counts	100 [%] 95 90 0	1,000 2,000 3,0 Full cycles [-]	100 95 90 90 0 1,000 1,0	0							
Single valuesSOHstate of health at readout[0, 100] (%)SOCstate of charge at readout[0, 100] (%)energy_throughputtotal battery energy throughput until readout[0, 8,000] (kWh)voltagebattery voltage at readout[0, 70] (V)currentbattery current at readout[-1,500, 1,500] (A)temperaturebattery temperature at readout[-126, 126] (°C)Histogram valuestime spent in SOC range [0, 10, 20,, 100] (%)[0, 2 ³² - 1] (s)time_temperature_x, x \in [1, 6]time spent in temperature range [,0, 0, 20,, >70] (°C)[0, 2 ³² - 1] (s)(dis)charge_temperature_x, x \in [1, 6]time spent in temperature range [,0, 0, 20,, >70] (°C)[0, 2 ³² - 1] (s)number_dod_x, x \in [1,7]number of DODs in range [0, 1.1, 2.2,, >9.9] (Ah)[0, 2 ³² - 1] (counts	Name		Description	Value range							
SOHstate of health at readout[0, 100] (%)SOCstate of charge at readout[0, 100] (%)energy_throughputtotal battery energy throughput until readout[0, 8,000] (kWh)voltagebattery voltage at readout[0, 70] (V)currentbattery current at readout[-1,500, 1,500] (A)temperaturebattery temperature at readout[-126, 126] (°C)Histogram valuestime_soc_x, $x \in [1, 10]$ time spent in SOC range [0, 10, 20,, 100] (%)[0, $2^{32} - 1$] (s)time_temperature_x, $x \in [1, 6]$ time spent in temperature range [,0, 0, 20,, >70] (°C)[0, $2^{32} - 1$] (s)(dis)charge_temperature_x, $x \in [1, 7]$ number of DODs in range [0, 1.1, 2.2,, >9.9] (Ah)[0, $2^{32} - 1$] (counts	Single values										
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energy_throughputtotal battery energy throughput until readout[0, 8,000] (kWh)voltagebattery voltage at readout[0, 70] (V)currentbattery current at readout $[-1,500, 1,500]$ (A)temperaturebattery temperature at readout $[-126, 126]$ (°C)Histogram valuestime_soc_x, x $\in [1, 10]$ time spent in SOC range $[0, 10, 20,, 100]$ (%) $[0, 2^{32} - 1]$ (s)time_temperature_x, x $\in [1, 6]$ time spent in temperature range $[0, 0, 20,, >70]$ (°C) $[0, 2^{32} - 1]$ (s)(dis)charge_temperature_x, x $\in [1, 6]$ time of DODs in range $[0, 1.1, 2.2,, >9.9]$ (Ah) $[0, 2^{32} - 1]$ (counts	SOC		state of charge at readout	[0, 100] (%)							
voltagebattery voltage at readout $[0, 70]$ (V)currentbattery current at readout $[-1,500, 1,500]$ (A)temperaturebattery temperature at readout $[-126, 126]$ (°C)Histogram valuestime_soc_x, x $\in [1, 10]$ time spent in SOC range $[0, 10, 20,, 100]$ (%) $[0, 2^{32} - 1]$ (s)time_temperature_x, x $\in [1, 6]$ time spent in temperature range $[0, 0, 20,, >70]$ (°C) $[0, 2^{32} - 1]$ (s)(dis)charge_temperature_x, x $\in [1, 7]$ number of DODs in range $[0, 1.1, 2.2,, >9.9]$ (Ah) $[0, 2^{32} - 1]$ (counts	energy_throughput		total battery energy throughput until readout	[0, 8,000] (kWh)							
currentbattery current at readout $[-1,500, 1,500]$ (A)temperaturebattery temperature at readout $[-126, 126]$ (°C)Histogram valuestime_soc_x, x \in [1,10]time spent in SOC range [0, 10, 20,, 100] (%) $[0, 2^{32} - 1]$ (s)time_temperature_x, x \in [1,6]time spent in temperature range [,0, 0, 20,, >70] (°C) $[0, 2^{32} - 1]$ (s)(dis)charge_temperature_x, x \in [1,6](dis)charge in temperature range [,0, 0, 20,, >70] (°C) $[0, 2^{32} - 1]$ (Ah) $[1,6]$ number_dod_x, x \in [1,7]number of DODs in range [0, 1.1, 2.2,, >9.9] (Ah) $[0, 2^{32} - 1]$ (counts	voltage		battery voltage at readout	[0, 70] (V)							
temperaturebattery temperature at readout $[-126, 126]$ (°C)Histogram valuestime_soc_x, x \in [1, 10]time spent in SOC range [0, 10, 20,, 100] (%) $[0, 2^{32} - 1]$ (s)time_temperature_x, x \in [1, 6]time spent in temperature range [,0, 0, 20,, >70] (°C) $[0, 2^{32} - 1]$ (s)(dis)charge_temperature_x, x \in [1, 6](dis)charge in temperature range [,0, 0, 20,, >70] (°C) $[0, 2^{32} - 1]$ (Ah)number_dod_x, x \in [1,7]number of DODs in range [0, 1.1, 2.2,, >9.9] (Ah) $[0, 2^{32} - 1]$ (counts	current		battery current at readout	[-1,500, 1,500] (A)							
Histogram values time_soc_x, x \in [1, 10] time spent in SOC range [0, 10, 20,, 100] (%) $[0, 2^{32} - 1]$ (s) time_temperature_x, x \in [1, 6] time spent in temperature range [,0, 0, 20,, >70] (°C) $[0, 2^{32} - 1]$ (s) (dis)charge_temperature_x, x \in [1, 6] (dis)charge in temperature range [,0, 0, 20,, >70] (°C) $[0, 2^{32} - 1]$ (Ah) $[1, 6]$ number_dod_x, x \in [1, 7] number of DODs in range [0, 1.1, 2.2,, >9.9] (Ah) $[0, 2^{32} - 1]$ (counts	temperature		battery temperature at readout	[-126, 126] (°C)							
time_soc_x, x \in [1, 10]time spent in SOC range [0, 10, 20,, 100] (%) $[0, 2^{32} - 1]$ (s)time_temperature_x, x \in [1, 6]time spent in temperature range [,0, 0, 20,, >70] (°C) $[0, 2^{32} - 1]$ (s)(dis)charge_temperature_x, x \in [1, 6](dis)charge in temperature range [,0, 0, 20,, >70] (°C) $[0, 2^{32} - 1]$ (Ah)number_dod_x, x \in [1, 7]number of DODs in range [0, 1.1, 2.2,, >9.9] (Ah) $[0, 2^{32} - 1]$ (counts)	Histogram values										
time_temperature_x, x \in [1,6]time spent in temperature range [,0, 0, 20,, >70] (°C) $[0, 2^{32} - 1]$ (s)(dis)charge_temperature_x, x \in (1,6](dis)charge in temperature range [,0, 0, 20,, >70] (°C) $[0, 2^{32} - 1]$ (Ah)[1,6]number_dod_x, x \in [1,7]number of DODs in range [0, 1.1, 2.2,, >9.9] (Ah) $[0, 2^{32} - 1]$ (counts	time_soc_x,x ∈ [1,10]		time spent in SOC range [0, 10, 20,, 100] (%)	[0, 2 ³² - 1] (s)							
(dis)charge_temperature_x, x ∈ (dis)charge in temperature range [,0, 0, 20,, >70] (°C) [0, 2 ³² - 1] (Ah) [1,6] number_dod_x, x ∈ [1,7] number of DODs in range [0, 1.1, 2.2,, >9.9] (Ah) [0, 2 ³² - 1] (counts	time_temperature_ $x, x \in [1, 6]$		time spent in temperature range [,0, 0, 20,, >70] (°C)	[0, 2 ³² - 1] (s)							
number_dod_x,x ∈ [1,7] number of DODs in range [0, 1.1, 2.2,, >9.9] (Ah) [0, 2 ³² - 1] (counts	(dis)charge_temperature_x, x ∈ [1,6]		(dis)charge in temperature range [,0, 0, 20,, >70] (°C)	[0, 2 ³² - 1] (Ah)							
	number_dod_ $x, x \in [1, 7]$		number of DODs in range [0, 1.1, 2.2,, >9.9] (Ah)	[0, 2 ³² – 1] (counts							

V. Steininger, et al., Cell Reports Physical Science 4, 101596, 2023.

CARL Electronic Systems

Center for Ageing, Reliability and Lifetime Prediction of Electrochemical and Power

Laboratory data for both calendar and cyclic aging



V. Steininger, et al., Cell Reports Physical Science 4, 101596, 2023.





Field data vs. laboratory data for aging diagnosis

- Field data from 600.000 vehicles
- Laboratory data from both calendar and cyclic ageing tests





Feature extraction framework to integrate laboratory and field data



V. Steininger, et al., Cell Reports Physical Science 4, 101596, 2023.



Transferable capacity estimation from laboratory to field

- Automatic feature extraction and dimension increasing with physical interpretation.
- Uncertainty awareness of charging protocols, charging habits and production quality.
 Only using 100 s charging data in the determined voltage window.



Q. Wang, et al., Applied Energy, 350, 121747, 2023.



Challenges in battery aging prediction





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Lifetime prediction from large-scale field data



Q. Wang, et al., Cell Reports Physical Science, 2023.



Battery end-of-life [km]

Data preprocessing and charging curve reconstruction





Statistical distributions of stress factors of vehicles with different ageing rates



Q. Wang, et al., Cell Reports Physical Science, 2023.



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Statistical feature engineering with multi-level strategy



Feature pool construction

Q. Wang, et al., Cell Reports Physical Science, 2023.



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Feature selection with correlation analysis



	T_mear	T_tota	lc_mear	lc_ma:	Ic_tota	acc_energy_ch	ld_ec_mear	ld_ec_tota	acc_energy_d_e	ld_er_mear	Id_er_tota	acc_energy_d_e	Id_tota	acc_energy_(Soc_mir	Vc_median_va	cyc_DOD_max	V_mear	с_ 	V_range		acc_run_time	acc_time	D calendar_time		Lota	Scion	~~	2025
I_total -	0.51	0.94	-0.15	0.2	-0.97	0.97	-0.023	1	1	-0.43	-0.91	0.91	0.99	0.99	-0.22	-0.16	0.28	0.058	-0.057	-0.028	-0.27	0.89	0.93	0.19	0.088	1			
ld_mean -	0.27	-0.15	-0.014	-0.23	-0.12	0.12	0.96	0.085	0.084	-0.26	-0.018	0.019	0.069	0.068	0.1	-0.056	-0.12	0.13	0.23	0.21	0.47	-0.35	-0.27	-0.43	1	0.088			
calendar_time -	-0.17	0.26	0.13	0.098	-0.1	0.098		0.19	0.19	-0.16	-0.32	0.32	0.23	0.23	-0.19	-0.037	0.1	-0.3	-0.3	-0.22	-0.29	0.38	0.35	1	-0.43	0.19			
acc_time -	0.36	0.96	-0.11	0.26	-0.88	0.88	-0.36	0.93	0.93	-0.31	-0.88	0.88	0.94	0.94	-0.24	-0.14	0.3	-0.0019	-0.15	-0.11	-0.43	0.99	1	0.35	-0.27	0.93			-0.75
acc_run_time -	0.31	0.93	-0.17	0.32	-0.82	0.82		0.89	0.89	-0.33	-0.87	0.87	0.9	0.9	-0.23	-0.16	0.3	-0.03	-0.19	-0.15	-0.48	1	0.99	0.38	-0.35	0.89			
V_var -	-0.24	-0.44	0.07	-0.15	0.2	-0.2	0.55	-0.28	-0.28	0.21	0.33	-0.33	-0.3	-0.3	0.062	0.24	-0.13	0.1	0.43	0.6	1	-0.48	-0.43	-0.29	0.47	-0.27			
V_range -	-0.0002	50.097	0.13	-0.18	-0.037	0.038	0.26	-0.036	-0.032	0.15	0.13	-0.13	-0.062	-0.059	-0.21	0.33	0.098	0.44	0.8	1	0.6	-0.15	-0.11	-0.22	0.21	-0.028			-0.50
V_max -	0.11	-0.098	0.2	-0.24	-0.017	0.019	0.3	-0.058	-0.049	0.2	0.19	-0.18	-0.094	-0.087	0.052	0.29	-0.071	0.79	1	0.8	0.43	-0.19	-0.15	-0.3	0.23	-0.057			
V_mean -	0.2	0.054	0.047	-0.017	-0.12	0.12	0.15	0.052	0.064	0.028	0.051	-0.044	0.025	0.036	0.12	0.13	-0.089	1	0.79	0.44	0.1	-0.03	-0.0019	-0.3	0.13	0.058			
cyc_DOD_max -	0.18	0.31	-0.015	-0.0041	-0.29	0.28	-0.15	0.27	0.27	-0.078	-0.24	0.24	0.27	0.27	-0.71	0.14	1	-0.089	-0.071	0.098	-0.13	0.3	0.3	0.1	-0.12	0.28			-0.25
- cyc_median_var -	-0.14	-0.16	0.36	-0.28	0.13	-0.14	0.013	-0.17	-0.17	0.24	0.16	-0.16	-0.17	-0.17	-0.31	1	0.14	0.13	0.29	0.33	0.24	-0.16	-0.14	-0.037	-0.056	-0.16			
SOC_min -	-0.091	-0.24	-0.17	0.1	0.24	-0.23	0.11	-0.22	-0.22	0.023	0.19	-0.18	-0.21	-0.21	1	-0.31	-0.71	0.12	0.052	-0.21	0.062	-0.23	-0.24	-0.19	0.1	-0.22			
acc energy d -	0.45	0.93	-0.15	0.21	-0.93	0.94	-0.055	0.99	0.99	-0.46	-0.95	0.95		1	-0.21	-0.17	0.27	0.036	-0.087	-0.059	-0.3	0.9	0.94	0.23	0.068	0.99			0.00
ld total -	0.45	0.93	-0.15	0.21	-0.93	0.93	-0.054	0.99	0.99	-0.46	-0.95	0.95	1	1	-0.21	-0.17	0.27	0.025	-0.094	-0.062	-0.3	0.9	0.94	0.23	0.069	0.99			
acc energy d er -	0.25	0.82	-0.17	0.24	-0.8	0.8	-0.14	-0.9	0.9	-0.57			0.95	0.95	-0.18	-0.16	0.24	-0.044	-0.18	.0.13	.0.33	0.87	0.88	0.32	0.010	0.91			
Id_er_mean -	0.25	-0.33	0.42	-0.41	0.35	-0.35	0.0051	-0.41	-0.41	1	0.57	-0.57	-0.46	-0.46	0.023	0.24	-0.078	0.028	0.2	0.15	0.21	-0.33	-0.31	-0.10	-0.26	-0.43			0.25
acc_energy_d_ec -	-0.51	0.94	-0.14	0.2	-0.96	0.96	-0.022	-0.47	-0.43	-0.41	-0.9	0.9	0.99	0.99	-0.22	-0.17	0.27	0.064	-0.049	-0.032	-0.28	0.89	0.93	0.19	0.084	-0.42			
ld_ec_total -	0.51	0.94	-0.14	0.2	-0.96	0.96	-0.021	1	1	-0.41	-0.9	0.9	0.99	0.99	-0.22	-0.17	0.27	0.052	-0.058	-0.036	-0.28	0.89	0.93	0.19	0.085	1			
ld_ec_mean -	0.24	-0.24	0.086	-0.34	-0.038	0.038	1	-0.021	-0.022	0.0051	0.14	-0.14	-0.054	-0.055	0.11	0.013	-0.15	0.15	0.3	0.26	0.55	-0.45	-0.36	-0.5	0.96	-0.023			0.50
acc_energy_chg -	0.59	0.92	-0.14	0.16	-1	1	0.038	0.96	0.96	-0.35	-0.8	0.8	0.93	0.94	-0.23	-0.14	0.28	0.12	0.019	0.038	-0.2	0.82	0.88	0.098	0.12	0.97			
Ic_total -	-0.6	-0.92	0.14	-0.16	1	-1	-0.038	-0.96	-0.96	0.35	0.8	-0.8	-0.93	-0.93	0.24	0.13	-0.29	-0.12	-0.017	-0.037	0.2	-0.82	-0.88	-0.1	-0.12	-0.97			
lc_max -	0.011	0.23	-0.58	1	-0.16	0.16	-0.34	0.2	0.2	-0.41	-0.24	0.24	0.21	0.21	0.1	-0.28	-0.0041	-0.017	-0.24	-0.18	-0.15	0.32	0.26	0.098	-0.23	0.2			0.75
lc_mean -	-0.16	-0.13	1	-0.58	0.14	-0.14	0.086	-0.14	-0.14	0.42	0.17	-0.17	-0.15	-0.15	-0.17	0.36	-0.015	0.047	0.2	0.13	0.07	-0.17	-0.11	0.13	-0.014	-0.15			
T_total -	0.61	1	-0.13	0.23	-0.92	0.92	-0.24	0.94	0.94	-0.33	-0.82	0.82	0.93	0.93	-0.24	-0.16	0.31	0.054	-0.098	-0.097	-0.44	0.93	0.96	0.26	-0.15	0.94			
T_mean -	1	0.61	-0.16	0.011	-0.6	0.59	0.24	0.51	0.51	-0.2	-0.25	0.25	0.45	0.45	-0.091	-0.14	0.18	0.2	0.11 -	0.00025	5-0.24	0.31	0.36	-0.17	0.27	0.51			1.00
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Q. wang, et al., Cell Reports Physical Science, 2023.



Uncertainty-aware degradation prediction



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Failure distribution is as important as lifetime prediction for warranty



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Artificial Intelligence for Batteries @ RWTH Aachen University



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