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Telemetry and battery state of health in electric fleets: theoretical foundations and a conceptual framework for technical-operational decision-making

Telemetria e estado de saúde de baterias em frotas elétricas: bases teóricas e um arcabouço conceitual para decisão técnico-operacional

Telemetría y estado de salud de baterías en flotas eléctricas: bases teóricas y un marco conceptual para la decisión técnico-operacional

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Abstract:
Fleet electrification shifts operational control from fueling logistics to energy governance and electrochemical degradation management. In this setting, battery state of health (SOH) underpins decisions related to reliability, uptime, and total cost of ownership. Estimating SOH in real operation is inherently more challenging than in laboratory conditions, because field usage is dominated by partial charging, thermal variability, heterogeneous power demands, and sensing and algorithmic constraints of the battery management system (BMS). Core lithiumion aging mechanisms are consolidated and the relationship between measurements, estimated states, and uncertainty is clarified, followed by a critical review of major SOH estimation families—experimental techniques, adaptive models, and data-driven approaches—with emphasis on their transferability to fleet environments. Building on international evidence from real-world datasets and on national contributions regarding vehicle IoT monitoring infrastructure, a conceptual technical-operational framework is presented to convert telemetry into defensible decisions: data qualification, health-indicator design, domain-shift validation, and preventive-intervention criteria, without reliance on proprietary case studies.

Keywords: lithium-ion batteries; electric fleets; telemetry; BMS; state of health; diagnostics; prognostics**.**

Resumo:
A eletrificação de frotas utilitárias desloca o eixo de gestão de abastecimento para a governança de energia e de degradação eletroquímica. Nesse contexto, a avaliação do estado de saúde da bateria (SOH, state of health) sustenta decisões sobre confiabilidade, disponibilidade e custo total de propriedade. A estimação de SOH em operação é intrinsecamente mais complexa do que em laboratório, pois o uso real é marcado por recargas parciais, variabilidade térmica, perfis de potência heterogêneos e limitações de sensoriamento e de algoritmos do sistema de gerenciamento de bateria (BMS, battery management system). Consolidam-se fundamentos do envelhecimento em baterias de íons de lítio e discute-se a relação entre medições, estados estimados e incerteza, com revisão crítica de famílias de métodos para SOH — técnicas experimentais, modelos adaptativos e abordagens orientadas por dados — enfatizando a transferibilidade para ambientes de frota. Com base em literatura internacional sobre dados de campo e em contribuições nacionais sobre infraestrutura IoT veicular, estrutura-se um arcabouço teórico-operacional para converter telemetria em decisão: qualificação de dados, desenho de indicadores de saúde, validação sob mudança de domínio e critérios de intervenção preventiva, sem dependência de estudo de caso.

Palavras-chave:
baterias íons de lítio; frotas elétricas; telemetria; BMS; SOH; prognóstico; diagnóstico.

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Resumen:
La electrificación de flotas utilitarias desplaza el eje de la gestión del abastecimiento hacia la gobernanza de la energía y de la degradación electroquímica. En este contexto, la evaluación del estado de salud de la batería (SOH, state of health) sustenta decisiones sobre confiabilidad, disponibilidad y costo total de propiedad. La estimación del SOH en operación es intrínsecamente más compleja que en laboratorio, pues el uso real está marcado por recargas parciales, variabilidad térmica, perfiles de potencia heterogéneos y limitaciones de sensorización y de algoritmos del sistema de gestión de baterías (BMS, battery management system). Se consolidan fundamentos del envejecimiento en baterías de iones de litio y se discute la relación entre mediciones, estados estimados e incertidumbre, con una revisión crítica de familias de métodos para SOH — técnicas experimentales, modelos adaptativos y enfoques orientados por datos — enfatizando la transferibilidad a entornos de flota. Con base en la literatura internacional sobre datos de campo y en contribuciones nacionales sobre infraestructura IoT vehicular, se estructura un marco teórico-operacional para convertir la telemetría en decisión: calificación de datos, diseño de indicadores de salud, validación bajo cambio de dominio y criterios de intervención preventiva, sin dependencia de estudio de caso.

Palabras clave:
baterías de iones de litio; flotas eléctricas; telemetría; BMS; SOH; pronóstico; diagnóstico.

Introduction

Fleet electrification represents a structural shift in availability and risk management. In thermal systems, degradation is usually interpreted by mileage, usage patterns, and maintenance; in systems based on lithium-ion batteries, performance changes due to electrochemical and thermal mechanisms sensitive to operational history. This shifts the decision-making focus to energy governance, recharging, and aging as variables directly associated with productivity.

From a systems perspective, a battery functions as an asset whose behavior conditions its operation. Useful capacity, power delivered, and safety depend on how the asset is used and monitored over time. For this reason, estimating lifespan and health is not simply a matter of reading a value: it involves inferring states in the presence of operational variability and uncertainty, both in the environment and in the estimation process itself.

In this environment, telemetry enables the continuous observation of electrical and thermal variables and charging events, creating conditions to anticipate failures, reduce inefficiencies, and guide interventions. However, the usefulness of this data depends on explicit criteria for collection, qualification, and interpretation, as well as verifiable hypotheses that connect signals to degradation mechanisms. Without this linkage, indicators tend to vary due to

noise, regime changes, and recording gaps, reducing comparability and transferability between vehicles, routes, and stations.

A conceptual framework for technical and operational decisions in electric fleets therefore requires explicitly defining observable limits of field data and conditions for the validity of inferences about battery health. Estimation of SOH (Standard Operating Hours) must consider degradation mechanisms, available measurements, and model hypotheses; methods applied outside the domain in which they were validated tend to produce unstable results that are not very useful for operational decision-making.

2. Fundamental concepts: what is measured, what is estimated, and what is decided.

Before discussing methods, it is necessary to separate three layers that, in practice, are often confused. The first is the measurement layer: current, voltage, temperature, power, and event logs (e.g., start and end of recharges). The second is the estimated states layer: values inferred by algorithms from measurements, such as the state of charge and the state of health. The third is the decision layer: rules and criteria that transform estimated states into operation and maintenance actions.

The system responsible for mediating these layers at the vehicle level is the **BMS** (*battery management system*), that is, the set of hardware and software that monitors the battery, imposes safety limits, and estimates relevant states. Depending on the design, the BMS measures parameters at the pack level and, in some cases, at the module and cell level. This detail is important: degradation is heterogeneous. Even when the user "sees" a single battery, the pack is a set of cells in series/parallel, with variations in manufacturing, temperature, and aging. This heterogeneity tends to manifest as voltage and internal resistance variations between cells, and can anticipate failures in ways that are not obvious to aggregate metrics.

Two estimated states dominate the operating language. The first is the **SOC** (*state)* . *State of Charge* (SOC): an estimate of "how much usable charge is still available," usually expressed as a percentage. SOC is estimated, not measured. Even in mature architectures, SOC can drift over time due to sensor noise, calibration errors, and changes in the pack itself. The second is **SOH** (*state of charge) . of Battery health (SOH*), or state of health: a measure of degradation that, in practical terms, seeks to answer "how much the battery has aged" and "how much is left until an acceptable operational limit". A common definition associates SOH with the ratio between current capacity and initial capacity; another associates it with the evolution of internal resistance, relating it to power loss and heating. Both definitions reflect a physical

fact: aging appears as a loss of capacity and an increase in resistances associated with charge transport and parasitic reactions.

For SOC and SOH to be more than just numbers, it is useful to introduce two operational concepts that tie signals to states. The first is the **open-circuit voltage** , **OCV** (*open- circuit voltage). Voltage (OCV*): the voltage that the cell exhibits after a sufficient resting period to reduce polarization effects. OCV is valuable because, in many chemistries, there is a relationship between OCV and SOC; however, the relationship depends on temperature, recent history, and aging. The second is Coulomb **counting** , that is, the integration of current over time to estimate charge variation. Coulomb counting is intuitive, but accumulates drift error and requires *anchoring* (such as OCV corrections at rest) to maintain consistency.

These definitions are more than just formalities. They determine where weaknesses arise in the field. If SOC derives from and SOH depends, directly or indirectly, on the quality of the SOC, then a substantial part of the battery health problem is actually an estimation governance problem: calibrating, auditing, and validating estimated states under real-world operation, without the controlled conditions of a laboratory.

3. Aging in lithium-ion batteries: mechanisms, dominant variables, and implications for telemetry.

Performance loss in lithium-ion batteries is inevitable and results from the interaction between chemistry, temperature, and usage profile. Inside the cell, parasitic processes compete with the desired reactions: the solid interfacial layer forms and thickens on the anode (SEI, *solid). electrolyte (interphase*), there is consumption of cycled lithium, degradation of the electrolyte and reduction of the active material; under specific conditions, deposition of metallic lithium (*lithium)* may occur. *plating*). The combined effect appears as a drop in usable capacity and an increase in effective internal resistances, with a direct impact on available power and heating under load (VETTER et al., 2005; BARRÉ et al., 2013).

From an operational standpoint, a battery doesn't "wear out" solely based on mileage. What accelerates or decelerates aging is the history of electrical and thermal demands, including SOC windows, current rates, and charging patterns. Therefore, degradation is rarely linear: two assets with the same total processed energy can age differently if exposed to different temperature conditions and charge/discharge regimes (ECKER et al., 2014). The practical consequence is that "capacity" and "power" do not follow a single curve; they shift along the path traveled, which requires caution when extrapolating short-term trends.

A classic distinction organizes this phenomenon without impoverishing reality: calendar aging and cycle aging. The former occurs even when the system is inactive and is sensitive to time, temperature, and SOC level; the latter results from repeated use, being influenced by depth of discharge, current rates (C-rate), and thermal dynamics. This separation is useful because it helps interpret signals: there is loss associated with remaining in unfavorable conditions, and there is loss associated with repeated electrochemical work. In real applications, the two components overlap and interact, requiring models and readings that treat variables in a coupled manner, rather than assuming independence (BARRÉ et al., 2013; ECKER et al., 2014).

Temperature, in particular, occupies a central place as it is simultaneously a boundary condition and a result of the operation itself. High currents increase resistive dissipation and can raise the internal thermal gradient; at low temperatures, kinetic limitations and the risk of aggressive recharging increase; at high temperatures, parasitic reactions and material degradation accelerate. Post-mortem and thermal scanning studies show that dominant mechanisms and aging rates change with the thermal regime, making temperature reading a structuring signal for inferring health, and not a secondary "metadata" (WALDMANN et al., 2014).

This set of facts imposes an important limitation on telemetry: electrochemical mechanisms are not directly observable in operation. What reaches the monitoring system are effects—voltage, current, temperature, behavior during recharging, and indirect indications of increased resistance. Robustness, therefore, depends on how this partial evidence is transformed into stable, sensitive, and comparable indicators between vehicles and conditions. The diagnostic literature emphasizes precisely this transition: instead of reducing health to a single number, the aim is to decompose degradation modes and recognize curve signatures and thermal behavior that carry information about the internal process (BIRKL et al., 2017; BERECIBAR et al., 2016). For fleets, the implication is objective: telemetry has value when it allows associating operational patterns with aging trends and, from this, supporting recharging, maintenance, and operational decisions with technical consistency.

4. So-ohm estimation: families of methods and what is lost when leaving the laboratory.

The literature has established a useful taxonomy for SOH (Social Obsession of Health). Critical reviews frequently point to two major groups: experimental techniques and adaptive

(or data-driven) models, with intersections resulting in hybrid approaches. The value of this taxonomy is not classificatory; it is epistemological. Each family defines the type of evidence that justifies the inference of health.

Experimental techniques include methods that depend on specific test conditions, such as full-cycle capacity measurements, electrochemical impedance spectroscopy (EIS, *electrochemical impedance spectroscopy). impedance Spectroscopy* and controlled internal resistance testing are valuable techniques due to their close approximation to physical phenomena. However, their cost and requirements make them difficult to apply continuously in fleets, where interruptions and controlled conditions are limited. The dilemma, therefore, is preserving physical data without requiring an onboard laboratory.

A bridge between laboratory and field is the use of curve analysis, such as *incremental capacity* **analysis** (ICA). *differential voltage analysis (DVA, differential voltage analysis*) and differential voltage analysis (DVA, *differential voltage analysis) voltage In simple terms, ICA observes* the derivative of capacitance with respect to voltage during charging; peaks and offsets carry information about internal changes. Under ideal conditions, ICA allows the identification of degradation patterns; in real-world conditions, the challenge lies in noise, sampling, and, above all, the fact that recharges are partial. Even so, the literature shows efforts to make ICA applicable to modules and packs through peak tracking and adaptations for embedded implementation.

Adaptive models range from physics-based models to data-driven models. A particularly influential set, due to its impact on BMS, is the use of filters and observers, such as the *extended Kalman filter* **(** *EKF*) . In a classic series applied to BMS, the EKF is used to estimate SOC and, in extensions, to infer capacity and power loss throughout aging, relying on equivalent models and parameter identification. The strength of this family is the compromise between interpretability and computational feasibility. The weakness is structural: the model needs to represent the system with sufficient fidelity, and the parameters need to be identifiable under the available data. In the field, with heterogeneous profiles and missing data, identifiability can degrade.

Data-driven models, in turn, shift the focus: instead of explicitly modeling electrochemistry, they learn a mapping between signals and health. This approach has gained traction in part due to work demonstrating predictive capabilities using early-life data to anticipate lifespan, opening the way for forecast-based maintenance and warranty. The risk, however, is generalization: models trained in specific regimes may fail when the domain

changes, a phenomenon particularly common in fleets, where routes, weather, charging habits, and hardware versions vary.

Between these extremes, hybrid approaches and strategies that explore "informational windows" of real-world use are growing. There are studies exploring ICA (Index of Care and Care) under partial recharging, using health indices derived from the segmented curve, combined with probabilistic inference. These strategies are promising because they acknowledge an operational fact: the fleet will not adapt to the method; the method needs to adapt to the fleet, preserving validity criteria.

A pragmatic interpretation emerges from this scenario. In fleet management, the best method is not the most sophisticated, but rather the most defensible under the given conditions and usage. "Defensible" means that the relationship between signal, indicator, and decision is stable under relevant variations, and that the uncertainty is known and manageable.

5. Telematics and field data: domain switching, signal quality, and inference governance.

The main difference between laboratory and field work is not just noise. It's the nature of the experiment. In the laboratory, the researcher decides the protocol; in the field, the protocol is a consequence of operation, infrastructure, and human behavior. This produces a domain shift problem: the distribution of observed data in operation is different from that on which many methods have been validated. Consequently, the external validity of indicators becomes the central issue.

Studies based on real data show how "good" indicators can be highly sensitive to uncontrolled factors, such as thermal seasonality. Analyzing field data from an electric vehicle charging pack reveals that performance indicators are significantly affected by seasonal temperature variations; simultaneously, system-level readings of differential voltage curves are proposed as a proxy for charging impedance, precisely to accommodate the real-world context in which impedance "appears" in charging data. This result has a direct implication: if an indicator varies strongly with the climate, it needs to be normalized, conditioned, or at least interpreted within a thermal context, otherwise it risks producing false alarms and wrong decisions.

Another aspect is the BMS's own ability to estimate states under field conditions. Recent work analyzing data from hundreds of vehicles over years discusses disparities between field data and laboratory test data and how these disparities affect SOH estimation. Furthermore, they propose a multi-modal estimation framework that exploits multiple signal sources to reduce the

weaknesses of a single channel. The underlying idea is simple and powerful: in the field, no single variable is sufficiently stable; robustness comes from informational redundancy and rigorous preprocessing.

Telematics adds a systems engineering component to the electrochemical problem. Reliable data requires a capture, transmission, and storage architecture that preserves temporal integrity, reduces losses, and allows for auditing. In the national context, there are relevant contributions focused on real-time monitoring infrastructure for battery-powered electric buses, with application in a living mobility laboratory, emphasizing IoT integration and continuous monitoring of operational variables. These contributions are important because they show that "how to collect" is part of "how to infer"; without a minimally consistent infrastructure, health methods become post-hoc exercises.

The dimension of state estimation also has a tradition in national research. Academic works in Brazil address SOC estimation based on current, voltage, and temperature measurements, using variants of the Kalman filter, reinforcing that, even at the conceptual level, SOC should be treated as an estimated state subject to uncertainty, and not as a direct measurement. By incorporating this view, telemetry ceases to be "monitoring" and becomes "governed inference": it defines what is measurable, what is estimable, what hypotheses support the estimate, and what limits are accepted to make a decision.

This shift is crucial for fleets. The value lies not in having a lot of data, but in knowing which data is comparable. Comparability, in the field, depends on selecting operating windows with sufficient conditions to extract health information. An example is recharging: under certain conditions, recharging segments crossing voltage ranges can be more informative than long histories of mixed use. Recent literature explicitly explores this logic by structuring pipelines for capturing recharging behavior, pre-processing to remove low-quality segments, and extracting indicators from consistent windows, with the goal of inferring SOH at scale.

6. A theoretical and operational framework for transforming telemetry into decisionmaking.

In fleet environments, the usefulness of telemetry depends less on the volume of data and more on the ability to support technically defensible inferences under uncontrolled conditions. This requires treating inference as an engineering product, that is, as a verifiable chain connecting observable signals, estimated states, and operational decisions. Current,

voltage, and temperature are measured quantities; SOC and SOH are states inferred from these measurements; maintenance, power constraints, recharge adjustments, and mission redistribution are actions. When these layers become blurred, decisions are made as if an estimated state were a direct measurement, without explicitly stating the assumptions, the domain of validity, and the quality of the data that support the number.

Within this chain, the foundation is data qualification. Telemetry needs to carry context and minimum reliability criteria, especially in real-world operation, where losses, noise, sensor drift, and recording gaps are frequent. Temporal integrity, physical coherence between variables (e.g., plausible voltage responses to current variations), completeness, and thermal consistency are not aesthetic refinements; they are conditions for the applied method to be compatible with the type of evidence available. Without this qualification, the system mixes incomparable regimes and tends to produce unstable signals with low transferability between vehicles, routes, and stations.

In this context, health indicators function better as intermediate objects than as an attempt to "summarize" the battery into a single value. Intermediate indicators capture trends under comparable conditions, allowing for more robust readings even when complete cycles are not present. Recharge segments in similar windows, persistent thermal patterns under equivalent regimes, and resistance proxies extracted from electrical behavior are examples of evidence that, when well-defined, can be validated and tracked over time. The gain is twofold: it improves interpretability (what exactly changed) and creates a practical mechanism to detect when a model is extrapolating, that is, operating outside the domain in which it was calibrated.

Validation, therefore, should not be limited to average performance. Fleets operate under changing domains: climate, load, power profile, driving style, and charging infrastructure alter the data distribution and system behavior. The evaluation needs to be stratified by relevant thermal regimes and operational profiles, and should explicitly address uncertainty. Safer decisions emerge from convergent evidence, not from an isolated point of state of affairs. When uncertainty grows due to a lack of qualified data or regime incompatibility, system confidence should decrease, and intervention recommendations should require additional evidence. This principle is consistent with both filter-based observers (where covariance is part of the state) and probabilistic approaches, where estimation without a measure of dispersion has little operational significance.

Finally, the framework needs to engage with lifecycle management and reliability engineering applied to the electrochemical domain. Prognosis and diagnosis only add value when they connect to operation, recharging, and maintenance decisions in a consistent and

auditable manner. In this view, telemetry is not a visualization layer; it is a mechanism for reducing variability and increasing predictability, aimed at preserving availability, controlling risk, and stabilizing performance throughout the asset's lifecycle.

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