

An AI-Enabled IoT Framework for Real-Time Battery Health Monitoring and Remaining Useful Life Prediction of Lithium-Ion Batteries in Electric Vehicles: A Comprehensive Review

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Abstract

The increasing number of electric vehicles (EVs) being adopted has made it necessary for battery management systems to go beyond simple protection and state-of-charge estimation and instead focus on continuous state-of-health (SOH) assessment, degradation forecasting, and prediction of remaining useful life (RUL). The ageing of lithium-ion batteries is caused by a combination of electrochemical, thermal, mechanical, and operational processes, which makes it hard to accurately predict their condition when they are being driven and charged under changing conditions. This review brings together the most recent developments in battery sensing, health indicators, data preprocessing, machine learning, deep learning, physics-informed learning, transfer learning, uncertainty-aware prognosis, Internet of Things (IoT) connectivity, edge-cloud computing, and digital twins. The existing literature is divided into five clear sections and is then used to develop an integrated AI-enabled IoT framework in which safety-critical decisions remain at the edge of the vehicle while at the same time fleet-wide model training, long-term RUL forecasting, and lifecycle analysis are carried out in the cloud. The review also looks at public battery datasets, evaluation methods, cybersecurity, explainability, and cross-chemistry generalisation. The synthesis reveals that for practical deployment of EVs it is necessary not only to have a low prediction error but also to ensure physical consistency, to provide calibrated uncertainty, to achieve computational efficiency, to have secure connectivity, and to be robust against shifts in battery chemistry, temperature, and usage domain. The framework thus offers a succinct reference architecture for real-time battery health monitoring and for predictive maintenance in connected electric vehicles.

Keywords: lithium-ion battery, electric vehicle, battery management system, artificial intelligence, Internet of Things, state of health, remaining useful life, predictive maintenance, edge computing, physics-informed learning.

I. Introduction and Review Scope

Lithium-ion batteries are the main electrochemical energy storage technology used in today's electric vehicles due to their high specific energy, high power capability, long cycle life, and good efficiency.

However, their performance does deteriorate as a result of calendar ageing and from repeated cycling, which leads to a reduction in available capacity, an increase in impedance, and eventually limits both the vehicle's range and its power capability. The battery management system (BMS) has to estimate not just the current operating conditions but also the battery's long-term health. Early studies demonstrated that information about the battery's lifetime could be obtained from its voltage and capacity characteristics well before substantial capacity loss occurred [1], while more recent reviews have stressed the importance of linking battery data, feature engineering, machine learning, and lifecycle decision making [5], [11], [34].

An effective prognostic system for electric vehicles needs to function under varying temperatures, different charging rates, levels of depth of discharge, a range of driving behaviours, and with respect to the battery chemistry. Although empirical models are cost-effective they may lose accuracy when operating outside of the calibrated conditions; electrochemical models offer a more solid physical interpretation but can be computationally intensive and require a large number of parameters. AI-based data-driven approaches are capable of providing powerful nonlinear mappings, but their reliability hinges on the data being representative and on its ability to generalise. It has been shown through domain-adaptive learning that SOH models can be transferred between different battery populations with less need for labelled data in the target domain [2], and recent research into smart BMS systems is increasingly incorporating AI/ML with connected vehicle architectures [31].

A. The scope of the review and its contributions

The review presents a structured narrative synthesis of the research concerned with battery ageing, sensing, SOH/RUL estimation, public datasets, machine learning, deep learning, physics-informed methods, transfer learning, uncertainty quantification, IoT monitoring, edge-cloud computing, digital twins, cybersecurity, and predictive maintenance. Instead of concentrating merely on model accuracy, the paper looks at the entire deployment chain: from sensing through to validation, feature extraction, health estimation, degradation forecasting, uncertainty assessment, communication and finally to maintenance decision. Its main contribution is a concise five-section arrangement which connects the various methods to a unified AI-enabled IoT reference architecture for connected EV batteries.

II. Battery Degradation, Health Indicators, and data Foundation

A. The mechanisms of degradation and definitions of health

The degradation of lithium-ion batteries is a combined electrochemical-thermal-mechanical process, and the main mechanisms involved are the growth of the solid-electrolyte interphase, the loss of lithium inventory, the loss of active material, lithium plating, electrolyte decomposition, structural damage, calendar ageing, and temperature-accelerated side reactions. Whenever reviews of the ageing of automobiles are examined, temperature, charge rate, depth of discharge, state of charge, and usage history are found to be the primary stress factors [6], [12], [25], [26]. Furthermore, new diagnostic studies make use of changes in electrode behaviour related to entropy, variations in thermal conductivity with ageing, and cell expansion or strain as additional signs of internal degradation [27], [28], [30].

Real-time battery operation also demands tracking of the state-of-charge (SOC). If discharge current is taken as positive, Coulomb counting can be written as

$$SOC(t) = SOC(t_0) - (\eta/C_n) \int_{t_0 \rightarrow t} I(\tau) d\tau \quad (1)$$

SOH is usually indicated by either retained capacity or by an increase in resistance. These are the two concise definitions

$$SOH_Q(k) = [Q_k / Q_{rated}] \times 100\% \quad (2a)$$

$$SOH_R(k) = [(R_{EOL} - R_k) / (R_{EOL} - R_0)] \times 100\% \quad (2b)$$

Remaining useful life is the interval between the current ageing state and the selected end-of-life (EOL) threshold:

$$RUL_k = k_{EOL} - k; \quad RUL(t) = t_{EOL} - t_{current} \quad (3)$$

Here Q_k and R_k present available capacity and internal resistance are given respectively, while Q_{rated} , R_0 , and R_{EOL} refer to the reference states. Since the EOL thresholds vary from manufacturer to manufacturer and depending on the second-life applications, the SOH and RUL should be understood in relation to the intended duty [19], [20]. The equivalent-cycle and fatigue-based lifetime models offer complementary baseline assessments which are based on physical considerations for cumulative ageing [22].

B. The detection of signals, preprocessing, and health indicators

The health indicators which are most practical to deploy are based on signals that are already available from the BMS—including cell voltage, pack current, temperature, the duration of charging and discharging, energy throughput, voltage dispersion, and the estimated internal resistance. Although supplementary methods such as impedance, strain, and thermal-property measurements can improve the sensitivity of the diagnosis, they also increase the cost of the equipment. Table I gives a summary of the most relevant measurements for AI-enabled monitoring.

$$Q_t h(t) = (1/3600) \int_0^t |I(\tau)| d\tau; \quad R_{int} \approx \Delta V / \Delta I \quad (4)$$

Signal / Indicator	Typical Source	Health Relevance
Cell voltage / voltage spread	BMS voltage-monitoring IC	SOC, imbalance, curve-shape ageing features
Pack current / C-rate	Shunt or Hall-effect sensor	Charge throughput and electrical stress
Temperature / temperature spread	NTC, RTD, thermocouple	Thermal stress and abnormal heating
Capacity / energy throughput	Derived from charge integration	Primary SOH and usage indicator
Internal resistance / impedance	Pulse model or EIS	Power fade and electrochemical ageing
Charge-time and curve features	BMS telemetry	IC/DV, CC-CV and data-driven features
Strain / expansion	Strain sensor	Cell swelling and structural ageing [30]

TABLE I. Typical battery signals and health indicators.

The raw EV telemetry has to be synchronized, have any missing values or outliers checked and filtered, be normalized, and then be divided into segments before AI inference can take place. Features that are useful include the charge duration at constant current or constant voltage, the voltage-rise time, the maximum and average temperature, the temperature gradient, the accumulated ampere-hour and energy

throughput, the depth of discharge, and the rest time. The incremental-capacity (dQ/dV) and differential-voltage (dV/dQ) curves can show peaks and changes in amplitude that are sensitive to ageing; interpretable feature engineering has also been used to improve cross-operating-condition lifetime prediction [16].

$$IC(V) = dQ/dV ; \quad DV(Q) = dV/dQ \quad (5)$$

$$F_k = [V_{mean}, \Delta V, I_{RMS}, T_{max}, \Delta T, Q_{th}, DoD, R_{int}, \dots]^T \quad (6)$$

C. Public Datasets and Validation

Open datasets are still essential for the development of algorithms; the NASA and CALCE datasets are commonly used in studies of state of health and remaining useful life, the Oxford Battery Degradation Dataset offers data from long-duration cycling [8], and the fast-charging dataset introduced by Severson et al. includes 124 LFP/graphite cells which were cycled using a number of fast-charge protocols [1]. The Battery Data Genome initiative advocates for greater standardization, improved metadata quality, and an interoperable battery data infrastructure [23]. Although these resources allow research to be reproduced, they do not fully replicate real EV operation, since in practice regenerative braking, partial cycling, changes in ambient temperature, long periods of rest, and loads that vary according to the driver all result in a significant domain shift.

Dataset / Resource	Main Content	Typical Use
NASA PCoE	Voltage, current, temperature, capacity ageing data	SOH/RUL benchmarking
Oxford [8]	Long-term lithium-ion cell cycling	Degradation and SOH validation
CALCE	Multiple cells and cycling protocols	SOH/RUL and transfer studies
Stanford-MIT [1]	124 LFP/graphite cells, diverse fast charging	Early lifetime prediction
Battery Data Genome [23]	Data principles and shared infrastructure	Standardization and cross-study reuse

TABLE II. Examples of battery ageing datasets and resources.

Validation must therefore be carried out at the level of individual cells rather than by randomly combining samples from the same cell into training and test sets. More rigorous forms of validation are those that are based on condition, temperature, chemistry, and also on a cross-dataset basis. These procedures are essential since the real aim is not just to achieve a low error rate with samples that are familiar from the laboratory but to make reliable predictions regarding a battery that has not been seen under real-world conditions.

III. Methods for estimating SOH and RUL using AI

A. Traditional machine learning and deep learning

Battery health estimation may be broken down into direct measurement, model-based estimation, classical machine learning, and deep learning. Equivalent-circuit and electrochemical models keep

physical meaning, whereas Kalman filters, particle filters, and observers are used for recursive state estimation. With data-driven methods, support-vector regression, random forests, gradient boosting, XGBoost, Gaussian processes, and artificial neural networks associate engineered features with SOH or RUL. Deep networks lessen the need for manual feature selection: CNNs pick up local curve patterns; RNNs, LSTMs, and GRUs deal with sequential degradation; CNN-LSTM structures combine the learning of local and temporal features; and transformers are able to capture longer-range dependencies. The example of online LSTM-based SOH identification shows that there is still interest in lightweight sequential inference [29].

$$\hat{y}_k = f_{\theta}(F_1:k), \quad \text{with } \hat{y}_k \in SOH_k, RUL_k \quad (7)$$

$$\text{Attention}(Q,K,V) = \text{softmax}(QK^T/\sqrt{d_k})V \quad (8)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t; h_t = o_t \odot \tanh(c_t) \quad (9)$$

The prediction provided by the RUL method is different from the current estimate of the state of health because errors build up over the forecast period. More recent studies have combined transformer or recurrent architectures with stochastic-process models in order to account for long-term degradation and uncertainty [7]. Reviews of methods for degradation assessment and predictive maintenance stress the need to report forecasting performance together with the prediction horizon, the uncertainty, and the definition of end-of-life [20].

B. Physics-Informed, Transfer, and Uncertainty-Aware Learning

Models that are based entirely on data might match the data from laboratory tests but could fail to respect the actual physical trends of degradation beyond the range of the training data. In order to overcome this, physics-informed neural networks incorporate physical equations, monotonicity constraints, mechanistic features, or hybrid model structures during the learning process. The general approach known as the physics-informed paradigm was established by Raissi et al. [15] and has since been applied to the task of battery state estimation [13], [14]. Ye et al. connected incremental-capacity and temperature-derived information to the estimation of the state of health using a physics-informed method [3], and other comparative studies have looked at the advantages and disadvantages of physics-informed machine learning for use in battery diagnostics [32]. Further evidence is provided by hybrid physics/data-driven electrochemical estimation, which shows that it is possible to learn the model residuals without giving up the physical structure [9]. More recent research has extended these ideas to include degradation-pattern decoupling and cross-chemistry prediction [4], [18].

$$L_{total} = \lambda_d L_{data} + \lambda_p L_{physics} + \lambda_m L_{mono} \quad (10a)$$

$$L_{mono} = (1/(N-1)) \sum_{k=1}^{N-1} \max[0, SOH_{k+1} - SOH_k]^2 \quad (10b)$$

Another important issue is dealt with by transfer learning and domain adaptation: a model that has been trained on one kind of cell, one temperature, one manufacturer, or one C-rate might not be able to be applied to a different one. Domain-adaptive deep learning has lessened the requirement for new labelled

degradation experiments [2], and feature-matching transfer learning has been used for capacity estimation among batteries [17]. This is particularly relevant in the case of fleet deployment, since labelled end-of-life data for every chemistry and vehicle variant are seldom available.

$$P_s(X, Y) \neq P_t(X, Y) \quad (11)$$

RUL ought best to be given in the form of a distribution or a confidence interval rather than as a single deterministic value. Methods for representing both epistemic and aleatoric uncertainty include physics-constrained Bayesian neural networks [21], uncertainty-aware explainable prediction [24], and probabilistic degradation assessment [33]. Uncertainty is especially important when near the end of life, under unseen operating conditions, or as sensor quality declines.

$$p(RUL|X, D) \rightarrow E[RUL|X, D], Var[RUL|X, D] \quad (12)$$

C. Comparative Assessment

Method	Strength	Main Limitation	Best Fit
SVR / tree ensembles	Good with modest data; efficient	Requires engineered features	SOH screening
Gaussian process / Bayesian	Natural uncertainty estimates	Scaling cost	RUL confidence bounds
CNN	Automatic local feature extraction	Limited long-range context	Curve-based SOH
LSTM / GRU	Sequential degradation modelling	Training and drift sensitivity	Online SOH/RUL
Transformer	Long-range dependency modelling	Memory/compute demand	Long-horizon forecasting
Transfer learning	Reduces target labels	Domain mismatch can remain	New chemistry/conditions
PINN / hybrid physics-AI	Physical consistency and extrapolation support	Constraint/model design complexity	Cross-domain prognosis
Ensemble / probabilistic	Robustness and uncertainty	Higher computational cost	Safety-critical prognosis

TABLE III. A compact comparison of the various AI methods for estimating battery health.

There is no one algorithm that is superior in all cases. As evidenced by research into fast-charging optimization, AI can be used to guide battery operation as well as merely diagnose degradation [10], and recent lifecycle reviews highlight the importance of integrated management covering the entire process from sensing to making decisions regarding second-life and maintenance [34]. It therefore follows that when choosing a model accuracy, inference latency, memory footprint, chemistry transferability, data

requirements, uncertainty quality, and interpretability should be taken into account rather than just the single RMSE value.

IV. An AI-enabled framework for the prognostics of EV batteries in real time

A. Layered Edge-Cloud Architecture

The synthesis of the reviews indicates that deterministic protection should stay within the BMS, that low-latency health inference should take place at the edge, and that the computationally intensive learning should be carried out in the cloud. This arrangement is in agreement with the recent smart-BMS concepts based on AI and ML [31] as well as with the wider viewpoint on lifecycle management of machine learning [34]. The suggested signal path is as follows: battery pack → sensing of voltage/current/temperature/impedance → BMS → signal conditioning and validation → edge feature extraction → lightweight AI → real-time determination of SOC and SOH and anomaly detection → vehicle gateway → secure wireless communication → cloud database → fleet-level processing → advanced physics-informed/sequence models → RUL distribution → explainability and confidence assessment → digital twin → predictive maintenance and validated model update.

$$x_t = [V_t, I_t, T_t, SOC_t, R_t, \Delta V_t, \Delta T_t, \dots]^T \quad (13)$$

$$SOH_{hat_t} = f_{\theta}(F_1:t) \quad (14)$$

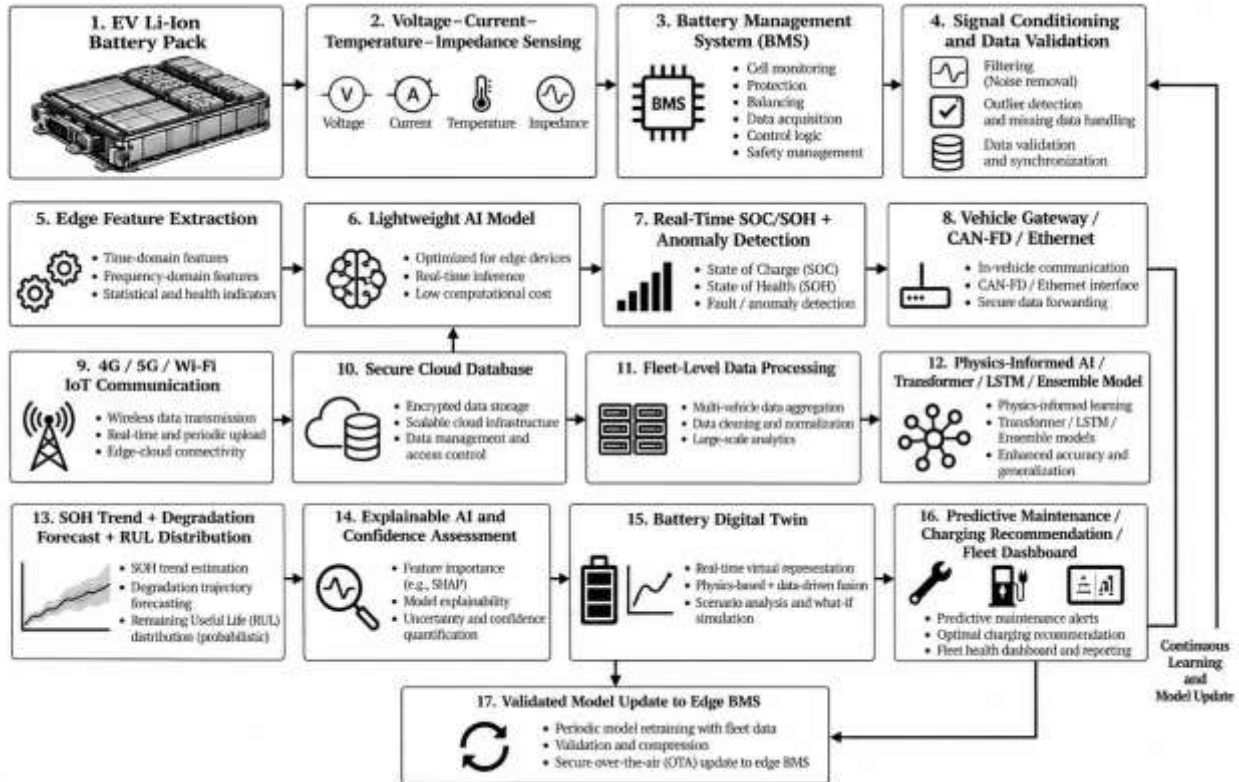


Fig. 1. An AI-enabled IoT architecture derived from a review, aimed at enabling real-time monitoring of EV battery health and prediction of its remaining useful life.

B. Edge Intelligence, Cloud Learning, and Digital Twin

The timestamps should be aligned, the data filtered, the sensors validated, the features extracted, the state of health inferred, any anomalies detected, and short-term local buffering carried out by the edge processing. Safety-critical operations must not rely on external connectivity. The cloud is capable of gathering information from a number of vehicles in order to carry out fleet-level degradation clustering, long-horizon RUL forecasting, model drift detection, computationally intensive retraining, and model-version management. A hybrid digital twin can integrate equivalent-circuit, thermal, ageing, and data-driven residual models, this being an approach that is in line with hybrid physics/data estimation [9].

$$At = \|xt - x^t\| \text{ or } At = g(xt, x^t) \quad (15)$$

Here, x_t is the actual measurement and $\hat{x}_t$ is the predicted or reconstructed value.

$$D_{fleet} = D_1, D_2, \dots, D_N \quad (16)$$

$$y_D T(t) = y_{physics}(t) + r_\theta[x_t] \quad (17)$$

A practical RUL engine should predict the future SOH trajectory based on the current state of health and the expected stress, and it should define the RUL as the first point in the future when the predicted trajectory reaches the predetermined end-of-life threshold; the output must include a confidence interval. In order to provide explainable outputs, it is possible to link abnormal degradation to sustained high temperature, to repeated high C-rate charging, to an increasing internal resistance, or to other major factors, in accordance with the uncertainty-aware and explainable approach described in [24].

$$SOH_h at_{t+h} = f(F_1: t, u_{t:t+h}) \quad (18)$$

$$RUL_h at = \min h \geq 0: SOH_h at_{t+h} \leq SOH_{EOL} \quad (19)$$

C. Communication, Security, and Federated Intelligence

In the vehicle, CAN/CAN-FD or automotive Ethernet can transmit validated telemetry to a gateway, with 4G/5G/Wi-Fi connectivity enabling the periodic upload of summarised health packets. The cloud should, where possible, receive only the data necessary for fleet analytics in order to reduce bandwidth usage and minimise privacy exposure. The implementation of connected battery monitoring brings with it a number of cybersecurity risks such as spoofed measurements, replay attacks, unauthorised access, malicious firmware updates, cloud compromise, denial-of-service attacks, and model poisoning. Secure boot, authenticated and encrypted communication, signed model updates, access control, logging, and anomaly monitoring should therefore be considered essential design requirements rather than optional features.

Federated learning is a promising development since the vehicles are able to update a shared model without having to transmit all of their raw telemetry data. Nevertheless, the problem of non-identically distributed vehicle data, the communication costs, the presence of malicious clients, and the need to synchronize the model updates are still to be resolved. The wider battery-data standardization initiative [23] together with the findings regarding transfer learning [17] indicate that practical fleet intelligence will rely on both secure data governance and on specific mechanisms for dealing with domain heterogeneity.

$$\theta_{global}^{(r+1)} = \sum_{i=1}^N [n_i / (\sum_j n_j)] \theta_i^{(r+1)} \quad (20)$$

D. The Results of Predictive Maintenance and Model Validation

The output should integrate SOH, RUL, anomaly scores, uncertainty, and model confidence to produce graded maintenance recommendations instead of using fixed universal thresholds. Batteries that are in normal condition can be left under routine monitoring, but if there is an acceleration of degradation, they should be inspected, and if there are significant thermal or resistance anomalies immediate diagnostics should be carried out. Cloud-trained models must be compressed or distilled in order to be used on the edge and should only be sent back to the BMS after having undergone offline validation, cybersecurity checks, version control, and a controlled over-the-air release. This closed loop transforms battery monitoring from a reactive form of protection into one that provides continuously improving prognostics.

V. Research Gaps, Next Steps, and Conclusion

A. Research Gaps

The biggest difficulty lies in the transition from laboratory conditions to real-world use. Although many models available in publications are trained on data from full cycles under controlled conditions, electric vehicle batteries instead experience partial cycles, regenerative braking, fluctuations in temperature, irregular fast charging, long periods without use, and imbalances between cells. Similar problems arise with cross-chemistry generalisation since the various chemistries—namely LFP, NMC, NCA, those with silicon blended in, and future types—have different voltage characteristics and ageing mechanisms. There is a lack of field-scale data on end-of-life situations, results obtained at the cell level do not automatically apply to complete battery packs, and static models tend to drift as the battery ages. It is precisely for these reasons that generalisation, physical consistency, and uncertainty are now becoming just as important as raw prediction error [5], [11], [32].

There is also the problem of inconsistent evaluation. In future studies it is necessary to report the chemistry, the cell count, the cycling protocol, the temperature range, the way in which the training and test sets are separated, the prediction horizon, the model size, the inference time, the errors in SOH and RUL, the confidence calibration, and the performance in the case of noisy or missing measurements. The capacity-retention figures should likewise be linked to the intended application, especially when the batteries are being considered for use in a second life [19].

$$MAE = (1/N) \sum_{i=1}^N |y_i - \hat{y}_i| \quad (21a)$$

$$RMSE = \sqrt{[(1/N) \sum_{i=1}^N (y_i - \hat{y}_i)^2]} \quad (21b)$$

$$MAPE = (100/N) \sum_{i=1}^N |(y_i - \hat{y}_i)/y_i| \quad (21c)$$

$$R^2 = 1 - [\sum_i (y_i - \hat{y}_i)^2 / \sum_i (y_i - \bar{y})^2] \quad (21d)$$

The prediction horizon and confidence-interval calibration should be given together with the point-error metrics for RUL models so that the accuracy and the quality of the uncertainty can be assessed together.

B. Future Research Directions

The key areas of focus are self-supervised learning based on large amounts of unlabeled fleet data; continual learning without suffering catastrophic forgetting; cross-chemistry transfer; the development

of physics-informed foundation models; the use of lightweight edge AI achieved through pruning, quantization, and knowledge distillation; federated learning; multimodal sensing; and uncertainty-aware maintenance. Trustworthy health models can be developed by combining degradation-sensitive thermal and mechanical signals [28], [30], interpretable operating-condition features [16], probabilistic prognosis [21], [33], and large interoperable data ecosystems [23]. Furthermore, fast-charging policy optimization [10] shows that there will be an important future shift from passive prognosis to health-aware control.

C. Conclusion

The review has condensed the existing body of work on lithium-ion battery health monitoring into five integrated sections covering degradation physics, sensing and datasets, AI methods, IoT/edge-cloud architecture, and future research. Even with reliable health indicators, conventional machine learning is still useful, whereas CNN, LSTM/GRU, and transformer models enhance the representation of nonlinear and temporal degradation. Methods that incorporate physical principles [3], [13]-[15], [18], [32], transfer learning [2], [17], and uncertainty-aware approaches [21], [24], [33] overcome the main limitations of purely data-driven prediction. The key insight with regard to deployment is that a practical solution for electric vehicles should integrate local BMS protection and edge inference with secure cloud-based fleet learning, digital-twin support, explainability, and controlled model updates. With such an architecture, battery management can be transformed from simple state monitoring to predictive, lifecycle-aware, and continuously improving EV battery intelligence.

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