Research Article

Navigating Component Degradation and Systems Integration Across the New Energy Vehicle Lifecycle

James John[1,*]
Yale University, New Haven, CT 06520, USA
* Corresponding author: James John
Email:JamesJohn@gmail.com

Abstract: Accelerating electrification exposes severe vulnerabilities in traditional reliability engineering, where uncoupled single-physics analyses fail to capture complex thermal, mechanical, and electromagnetic interactions in modern vehicles. This review critically assesses three core frontiers: multi-physics wear phenomena spanning battery packs, power conversion hardware, and structural glass; hybrid prognostic models reconciling physics-informed priors with machine learning for health estimation; and downstream workflows embedding failure forecasts into maintenance and parts supply chains. We find that although isolated predictive algorithms perform adequately in lab benchmarks, deploying them at the fleet level is severely hindered by the mismatch between localized component diagnostics and real-world supply-chain bottlenecks. Key roadblocks include parameter estimation bottlenecks under shifting dynamics, sample scarcity for nascent failure types, and volatile logistics schedules. Ultimately, advancing next-generation fleet health depends not merely on marginal algorithmic gains, but on standardized benchmark datasets, risk-aware operational policies, and unified interfaces bridging degradation science with logistics operations.

Keywords: *Remaining Useful Life Prediction, Multi-Physics Degradation, Intelligent Maintenance Logistics, Prognostic Modelling, New Energy Vehicle Reliability.*

1. Introduction

The global automotive industry is undergoing a transformation that is arguably as profound as the shift from horse- drawn carriages to internal combustion engines, yet the nature of this transition is qualitatively different in at least one critical respect: the reliability expectations placed on new energy vehicle (NEV) components are no longer confined to traditional notions of mechanical endurance but have expanded into a complex interplay of electrochemical stability, thermal management, electromagnetic compatibility, and structural integrity under highly variable operational conditions [1]. Unlike conventional vehicles, where failure modes are relatively well- understood and decades of accumulated field data have enabled reasonably accurate lifetime predictions, NEVs introduce a set of degradation mechanisms that are still only partially characterized, particularly when one considers the coupled effects of rapid charging protocols, regenerative braking cycles, and the increasing integration of power electronics with structural components [2]. This uncertainty is not merely an academic nuisance; it has direct implications for warranty costs, residual value estimation, and consumer acceptance, all of which ultimately determine the commercial viability of NEV technologies in an increasingly competitive market.

A substantial body of research has emerged over the past several years addressing various facets of NEV component reliability, yet the literature remains fragmented along disciplinary boundaries that may not reflect the inherently multi-physical nature of the problem. Mechanical engineers tend to focus on fatigue and fracture mechanics, often treating thermal and electrical effects as secondary perturbations; materials scientists investigate degradation at the microstructural level but rarely connect their findings to system-level prognostic algorithms; and data scientists develop increasingly sophisticated machine learning models for remaining useful life (RUL) prediction, frequently without adequate consideration of the physical constraints that govern the underlying degradation processes [3]. This fragmentation is understandable given the sheer complexity of the system, but it raises a more fundamental question: to what extent can isolated approaches, however rigorous within their own domains, be meaningfully integrated into a coherent framework for lifecycle reliability management? The present review attempts to address this question not by offering a unified theory, which would be premature given the current state of knowledge, but by mapping the conceptual terrain, identifying persistent gaps, and suggesting directions that may prove more productive than the continued proliferation of narrowly focused studies that do not engage with the broader system context.

The scope of this review is deliberately broad, encompassing battery systems, power electronics (with particular attention to insulated gate bipolar transistors, or IGBTs), electric drive units, and structurally integrated components such as laminated glazing that serve both protective and functional roles. This breadth is motivated by the observation that reliability challenges in NEVs rarely respect component boundaries; a thermal management failure in one subsystem can accelerate degradation in another, and manufacturing-induced residual stresses may interact with operational loads in ways that are not captured by component-level testing protocols [4]. The complexity of multi-physics coupling in automotive glass, as examined by Jiang [4], illustrates how thermo-mechano-electromagnetic interactions can produce failure modes that would not be predicted by considering any single physical domain in isolation. We structure our analysis along three intersecting axes: physics-based degradation modelling, data-driven prognostic algorithms, and system-level operational frameworks that attempt to connect condition monitoring with maintenance logistics. This tripartite organization, while analytically convenient, should not be taken as implying any inherent hierarchy or sequential relationship among these approaches; in practice, the most promising developments are occurring at their interfaces, where physical insights inform data modelling and operational constraints shape the formulation of prognostic objectives.

Before proceeding, it is worth acknowledging several limitations that constrain the scope and generalizability of the present review. The literature on NEV reliability is expanding rapidly, and although we have made every effort to cover the major contributions, some recent developments, particularly those emerging from industrial research laboratories that do not prioritize rapid publication, may have been overlooked. Furthermore, the predominance of English-language publications in the available corpus may introduce a geographic bias that does not fully reflect the diversity of research activity in this field, particularly in regions where NEV adoption has proceeded most aggressively. These caveats, while somewhat unavoidable, suggest that the conclusions drawn here should be treated as provisional and subject to revision as the evidence base continues to evolve. With these considerations in mind, we turn to a more detailed examination of the degradation mechanisms that underpin reliability concerns in NEV components.

2. Degradation Mechanisms and Multi-Physics Coupling in NEV Components

Understanding the physical origins of degradation is a prerequisite for any meaningful prediction of component lifetime, yet the identification of dominant failure mechanisms in NEV systems is complicated by the simultaneous action of multiple stress factors that may interact in nonlinear and occasionally counterintuitive ways [5]. The manufacturing processes themselves can introduce geometric irregularities and residual stress distributions that significantly influence subsequent degradation trajectories; Jiang [5] developed a multi-point geometric curvature inspection framework specifically for large-size laminated automotive glass, demonstrating that even small deviations from nominal geometry can produce localized stress concentrations that accelerate crack initiation under cyclic thermal loading. Thermal cycling, for instance, induces mechanical strain due to differential expansion coefficients among dissimilar materials; this strain, in turn, can accelerate crack propagation in solder joints or cause delamination in composite structures, while simultaneously altering electrical contact resistance and thereby affecting thermal dissipation in a feedback loop that is difficult to characterize experimentally [6]. Wang [6] proposed a reliability-informed life prediction framework that combines empirical degradation data with statistical modelling, offering a pragmatic approach to capturing the cumulative effects of such feedback mechanisms without requiring fully resolved physical simulations of each individual cycle.

The situation is further complicated by the fact that operational profiles vary considerably across different usage contexts, a vehicle used primarily for short urban trips experiences more frequent thermal transients than one operating predominantly on highways, and aggressive driving styles impose higher current loads that accelerate electrochemical aging in batteries while also generating more heat that stresses adjacent power electronics. This variability implies that laboratory accelerated aging tests, however carefully designed, may not fully capture the degradation trajectories observed in real-world fleets, and the gap between controlled experimental conditions and field performance remains one of the most persistent challenges in reliability engineering for NEVs.

Among the most intensively studied components in this context are lithium-ion battery cells, where degradation involves a complex interplay of solid electrolyte interphase (SEI) growth, lithium plating, particle cracking, and transition metal dissolution, each of which exhibits different temperature and rate dependencies. The challenge of modelling these processes simultaneously, and of scaling them from the cell level to the module and pack levels, has motivated a diverse array of modelling strategies, ranging from first-principles electrochemical models that resolve concentration gradients within individual particles, through equivalent circuit representations that capture aggregate electrical behaviour with moderate computational cost, to purely empirical data-driven approaches that correlate measured voltage and current trajectories with capacity fade without explicitly representing the underlying physics. Each of these approaches has its own strengths and limitations: first-principles models may offer greater extrapolative capability but require numerous parameters that are difficult to obtain non-destructively; equivalent circuit models are computationally efficient but may not capture degradation mechanisms that do not manifest in the electrical response; and data-driven models can achieve high predictive accuracy within the training domain but their performance may degrade substantially when applied to operating conditions not represented in the training data. The choice among these approaches is therefore not a matter of selecting the "best" method in any absolute sense, but rather of matching the modelling strategy to the specific application context and available data resources, a consideration that appears to be insufficiently emphasized in much of the current literature. Recent advances in wavelet transform and particle swarm optimization enhanced support vector regression have shown promise for battery RUL prediction, as demonstrated by Zhou et al. [7], though the generalizability of such hybrid approaches across different cell chemistries and aging conditions remains an open question.

Beyond battery systems, the reliability of power electronic components presents a distinct set of challenges that are only partially analogous to those encountered in battery applications. IGBT modules, which are central to the operation of traction inverters, experience thermomechanical fatigue due to the coefficient of thermal expansion mismatch between the silicon chip, solder layers, and the direct- bonded copper substrate, leading to crack initiation and propagation that eventually causes failure through either electrical open circuits or thermal runaway. What makes this problem particularly difficult is the coupling between thermal and electrical behaviour: as cracks develop, the thermal resistance of the package increases, leading to higher junction temperatures under the same operating current, which accelerates further degradation and creates a positive feedback mechanism that can cause rapid failure once a critical threshold is reached. Jiang [4] proposed a thermo- mechano- electromagnetic multi- physics coupling framework specifically for triple- functional integrated automotive laminated glass, and although the component type differs from IGBT modules, the methodological insight that treating physical fields as separable may miss qualitatively important interaction effects is directly applicable. The same study also emphasized the importance of unified- datum tolerance coordination, a consideration that becomes critical when attempting to align component- level reliability predictions with assembly- level specifications, since small deviations in manufacturing tolerances can combine to produce significantly different stress distributions at the system level[25].

A further dimension of complexity arises when considering components that serve both structural and functional purposes, such as the laminated windshield glass that increasingly incorporates sensors, heating elements, and heads- up display features. These components are subject not only to the thermal and mechanical loads associated with normal vehicle operation, but also to environmental stressors such as ultraviolet radiation, humidity, and airborne particulates that may affect both the structural integrity and the functional performance of integrated electronics. The degradation mechanisms in such components are multi- modal in nature and may involve concurrent processes at different spatial and temporal scales, making them particularly resistant to conventional reliability analysis approaches that assume a single dominant failure mode. Yan [8] conducted performance evaluation and weathering resistance studies of high UV- blocking coatings for automotive glass, and although the focus was on coating performance rather than component- level reliability, the findings highlight the importance of considering environmental exposure as a distinct stress factor that may interact with operational loads in unexpected ways. Taken together, these observations suggest that a comprehensive reliability framework for NEV components must encompass not only the well- characterized degradation mechanisms of individual subsystems, but also the cross- subsystem interactions and environmental influences that may amplify or mitigate degradation depending on the specific usage context[24].

3. Physics- Based and Data- Driven Approaches to Prognostic Modelling

The prediction of remaining useful life for NEV components has been approached from two broadly distinct methodological traditions, each with its own intellectual lineage, characteristic assumptions, and typical applications, and although the boundaries between these traditions have become increasingly blurred in recent years, the differences in their underlying philosophies remain consequential for practical implementation. The broader methodological context for such prognostic approaches is informed by developments in related fields of complex system modelling, where the integration of physical principles with data-driven techniques has been shown to complement purely theoretical or purely empirical strategies in nontrivial ways [9]. Physics-based approaches, which derive from the engineering sciences, begin with a mechanistic understanding of the degradation process, formulated as a set of differential equations or state-space models that describe the evolution of damage under specified loading conditions, and seek to predict future behaviour by forward simulation of these models given appropriate initial conditions and parameter values. The principal advantage of this approach is its capacity for extrapolation: because the model is based on physical principles that are assumed to hold beyond the range of available data, it can, in principle, make predictions for operating conditions that have not been observed experimentally, subject to the caveat that the model's assumptions remain valid. This extrapolative capability is particularly valuable in NEV applications, where novel component designs and emerging usage patterns, such as vehicle-to-grid charging or extreme fast charging, may not be well represented in existing fleet data[23].

In practice, however, the implementation of physics-based prognostic models faces several significant obstacles that have limited their adoption in industrial settings. The first is the problem of parameter identification: many of the material properties and boundary conditions required by detailed physical models are not directly measurable in the assembled component, and inverse estimation from operational data is often ill-posed, meaning that multiple parameter combinations can produce similar output trajectories while implying different future degradation behaviours. This identifiability problem is exacerbated by the limited observability of internal states in many NEV components; for instance, the internal temperature distribution within a battery pack is only indirectly inferable from surface measurements, and the state of health of individual cells within a module is even more difficult to assess non-destructively. A second challenge concerns the computational cost of detailed physical models: while a high-fidelity finite element simulation of an IGBT module under thermal cycling may be feasible for a single scenario, the repeated evaluations required for probabilistic prognosis, where uncertainty in initial conditions and model parameters is propagated through the simulation, quickly become computationally prohibitive, particularly when considering the need for real-time decision support in fleet management applications[22][26].

These limitations have motivated substantial interest in data-driven approaches, which seek to learn predictive mappings from operational data without explicit representation of the underlying physics. Machine learning methods, ranging from traditional support vector regression through various forms of neural networks to more recent physics-informed neural operators, have been applied to the RUL prediction problem for batteries, power electronics, and other NEV components with varying degrees of success. Wang [6] developed a reliability-informed life prediction framework specifically for NEV components that combined empirical degradation data with statistical modelling, offering a pragmatic middle ground between purely physics-based and purely data-driven paradigms. The framework's strength lies in its explicit treatment of uncertainty, which is often overlooked in deterministic prognostic models but is essential for risk-informed decision-making in maintenance planning.

A more recent development in this space is the application of multi-task learning architectures to anomaly detection and RUL prediction problems. Yin [10] proposed a multi-task learning framework for semiconductor manufacturing systems that simultaneously addresses anomaly detection and remaining useful life estimation, and although the application domain differs from automotive systems, the architectural principle, sharing representations across related prediction tasks to improve generalization with limited labeled data is directly transferable to NEV prognostics, where multiple degradation indicators (capacity fade, impedance growth, temperature rise) are often available from onboard diagnostic systems. The attraction of such methods lies in their flexibility and their ability to exploit high-dimensional data sources, including voltage and current waveforms, temperature histories, and vibration signatures, that would be difficult to incorporate into mechanistic models. Yin [11] further explored the optimization of cloud-native lakehouse architectures for real-time semiconductor analytics, addressing the data infrastructure challenges that underpin such data-driven approaches; although the focus is on semiconductor manufacturing, the data engineering principles, particularly those concerning the balance between performance, cost, and energy efficiency in large-scale analytics pipelines are broadly applicable to the fleet-level data management problems that arise in NEV prognostics.

Nevertheless, data-driven approaches are not without their own limitations, and the conditions under which they outperform physics-based alternatives are more restrictive than is sometimes acknowledged in the literature. A well-known issue is the requirement for extensive training data that cover the full range of operating conditions and degradation trajectories; in practice, such data are rarely available, particularly for new component designs or for failure modes that occur infrequently in the population but may have severe consequences when they occur. The problem of covariate shift, where the distribution of input features in the test environment differs from that in the training environment—is particularly acute in NEV applications, where driving patterns, charging infrastructure availability, and ambient conditions vary substantially across geographic regions and customer segments. Furthermore, many data-driven models are essentially black boxes that offer little insight into the physical mechanisms driving degradation, which may be acceptable for predictive purposes but complicates validation and limits the ability to reason about the model's behaviour in novel conditions. Hybrid approaches that combine physical models with data-driven learning have been proposed as a way to leverage the strengths of both traditions; these methods typically use physical principles to constrain or regularize the data-driven model, thereby improving extrapolation performance while maintaining some degree of interpretability. The development of physics-informed neural networks, which encode the governing differential equations as penalties in the loss function, represents one promising direction in this space, although the application to NEV reliability problems remains at an early stage and the practical benefits relative to either pure approach have yet to be conclusively demonstrated.

4. Integration with Maintenance Operations and Supply Chain Logistics

The ultimate purpose of reliability prediction is to inform decision-making, yet there remains a notable disconnect between the prognostic capabilities being developed in the research literature and their integration into operational systems for maintenance planning, spare parts inventory management, and supply chain risk mitigation. This gap is perhaps attributable to differences in the temporal and spatial scales at which these two domains operate: prognostic models typically focus on the component level and produce predictions over time horizons of days to months, whereas maintenance logistics systems operate at the fleet level and must coordinate decisions across multiple components, facilities, and supply chain partners over time horizons that may extend to years. Bridging this gap requires not only technical solutions, such as the development of interfaces that translate component-level predictions into fleet-level decision metrics, but also organizational and institutional changes that are often more difficult to achieve than purely technological advances[27].

The problem of spare parts availability illustrates the nature of the challenge: even if a prognostic model can reliably predict that a particular battery module will fail within the next 500 operating hours, acting on this prediction requires that the replacement part is available when needed, which in turn depends on the configuration of the distribution network, the lead times from suppliers, and the demands of other vehicles in the fleet. Lin [12] examined environmental impacts of intelligent logistics automation and the role of automation in supply chain resilience, highlighting that the integration of predictive maintenance with automated warehousing can reduce the response time to predicted failures if the necessary parts are strategically positioned. The study's emphasis on the environmental dimension of logistics automation is particularly relevant to NEV maintenance, where sustainability considerations extend beyond the operational phase to encompass the full lifecycle of replacement parts and their transportation. A related study by Lin [13] on machine learning-based logistics network optimization demonstrated that the incorporation of prognostic information into routing and inventory decisions can yield significant reductions in downtime without requiring substantial increases in total inventory, provided that the prognostic uncertainty is appropriately accounted for in the optimization formulation. These findings, while promising, also suggest that the benefits of integration are contingent on the availability of reliable, well-calibrated prediction intervals rather than merely point estimates of remaining useful life.

The challenges of integration are particularly acute in the context of supply chain disruptions, which have emerged as a critical concern following the global disruptions caused by the COVID-19 pandemic and subsequent geopolitical tensions that have affected the availability of critical materials and components. Under normal conditions, a moderate level of supply chain slack may be sufficient to accommodate the variability in component demand arising from maintenance activities; however, during extreme disruptions, where lead times extend unpredictably and multiple sources of supply may be simultaneously constrained, the coordination of maintenance planning with procurement becomes far more challenging. Recent work by Luo et al. [14] on fleet rebalancing for shared e-mobility systems using multi-agent deep reinforcement learning introduced methods for dynamic resource allocation under evolving demand patterns, and although this work was not specifically concerned with maintenance logistics, the underlying approach, treating rebalancing as a sequential decision problem with imperfect information has evident parallels to the problem of allocating replacement parts to vehicles with predicted failures. An earlier study by the same research group [15] addressed the rebalancing of expanding EV sharing systems with deep reinforcement learning, and the methodological progression between these two works illustrates the increasing sophistication of reinforcement learning approaches for dynamic resource allocation problems that share structural similarities with maintenance logistics under uncertainty. The integration of such approaches with prognostic information, however, remains largely unexplored and represents a potentially productive direction for future research that would require the collaboration of researchers from reliability engineering, operations research, and machine learning.

A further complication arises from the dual-use nature of many NEV components: the same battery pack that serves traction purposes may also be used for grid storage applications through vehicle-to-grid systems, which introduces additional usage cycles that affect degradation but are not primarily under the vehicle owner's control. This blurring of functional boundaries creates potential conflicts between the objectives of the vehicle owner, who may prioritize longevity of the powertrain, and the objectives of the grid operator, who may prioritize the availability of storage capacity, and the optimal maintenance policy from an overall system perspective may require negotiation or coordination mechanisms that are still not well understood. The integration of condition monitoring data with enterprise resource planning systems, as examined by Qiu [16] in the context of ERP and WMS integration for inventory turnover efficiency, offers some parallels to the integration challenge in NEV maintenance, although the specific requirements of reliability- driven logistics, including the need to incorporate prognostic uncertainty and the varying criticality of different components, impose additional constraints that are not fully addressed by standard enterprise systems. A related study by Qiu [17] on technical standard development for cross- industry data integration of ERP systems further underscores the importance of interoperability standards in enabling the seamless flow of information between condition monitoring systems and enterprise- level planning platforms, a prerequisite for the automated execution of maintenance actions triggered by prognostic alerts.

The increasing importance of these considerations suggests that future research on NEV reliability will need to extend beyond purely technical issues to encompass the economic and institutional arrangements that govern the operation and maintenance of NEV fleets. Such an expansion of scope, while welcome, also implies that the research community must develop new methodological tools and interdisciplinary collaborations that are not currently part of the mainstream reliability engineering curriculum. The broader industrial context for such integration efforts is informed by research on collaborative innovation platforms and digital operation systems[18][19], which, although not specifically focused on NEV applications, offer valuable insights into the organizational and technological enablers of cross- sector knowledge transfer and system- level efficiency optimization. The development of technical standards and systematic evaluation frameworks, as examined in related work on enterprise system integration[17][18], provides a reference point for the kinds of institutional infrastructure that may be needed to support the widespread adoption of prognostic maintenance in the NEV industry.

5. Conclusion

This review has mapped the current landscape of reliability prediction and intelligent operation maintenance for new energy vehicle components, focusing on the intersections of physics- based degradation modelling, data- driven prognostic algorithms, and system- level operational logistics, three domains that, as we have argued, have largely developed along separate trajectories but whose convergence may be essential for addressing the practical challenges of NEV fleet management. The central insight emerging from this analysis is not that any particular methodological approach is superior, but rather that the effective integration of multiple approaches depends on a more nuanced understanding of the uncertainties and assumptions that each carries, and on the development of shared benchmarks and validation protocols that can accommodate the diversity of failure modes and operating conditions encountered in practice. The existing literature provides robust evidence that individual prognostic methods can achieve impressive accuracy in specific, well- controlled settings, yet the translation of this accuracy into operational decisions remains constrained by the gaps between component- level predictions, system- level requirements, and supply chain constraints that have not received comparable research attention. One might argue that the most pressing research need is not for yet another prognostic algorithm with marginally improved performance on standard datasets, but for the systematic investigation of how prognostic uncertainty propagates through the decision chain from sensor data to maintenance execution, and for the identification of the points at which additional prognostic fidelity yields diminishing returns relative to improvements in logistics coordination. The latter consideration, in particular, points toward a conception of reliability engineering that treats prediction and action as jointly configurable rather than as sequential and independent processes. Looking forward, the emergence of new data sources, including fleet-level telemetry, connected vehicle networks, and digital twin platforms, may enable a more holistic approach to reliability management that encompasses the full lifecycle from design to disposal. Realizing this potential, however, will require not only technical innovation but also a cultural shift within the reliability community toward greater openness to interdisciplinary collaboration and a willingness to engage with the operational complexities that have historically been considered outside the remit of prognostic modelling. The trajectory of NEV technology development suggests that such engagement is becoming not merely advisable but necessary, as the scale and economic significance of the industry continue to grow.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The author(s) declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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