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Predictive Reliability Modeling in Distributed EV Charging Systems

Abstract
Distributed EV charging systems are becoming reliability-sensitive infrastructure in which charger availability, service continuity, and failure behavior vary across nodes under different load and stress conditions. Existing studies have addressed charging-behavior prediction, duration forecasting, flexibility estimation, charging-performance modeling, and infrastructure reliability assessment, showing that data-driven methods are valuable for interpreting heterogeneous charger operation. However, the literature remains fragmented across usage prediction, performance forecasting, and reliability analysis, leaving a gap in unified frameworks that connect distributed charger-state variables, degradation behavior, and predictive failure evolution. To address this issue, this article presents a reliability-modeling and failure-prediction framework based on rolling reliability state vectors, degradation-index forecasting, distributed node coupling, behavioral reliability classification, and failure-probability estimation. The results show distinct reliability trajectories under varying stress conditions, progressive failure-probability growth in vulnerable nodes, and declining service stability under degradation-sensitive behavior. Overall, the study demonstrates that predictive reliability modeling can support reliability-aware operation and maintenance planning in distributed EV charging networks.
Keywords: electric vehicle charging systems, reliability modeling, failure prediction, distributed charging networks, degradation forecasting, service stability.

1. Introduction

Distributed EV charging systems are becoming reliability-sensitive infrastructure because charging availability now depends on the combined behavior of chargers, ports, controllers, communication links, and user-driven operating variability across geographically dispersed nodes [1]. Reliability-related evidence from large-scale charging-station analysis shows that infrastructure quality is not defined only by installed capacity, since practical dependability is shaped by outage patterns, user experience, and persistent service failure signals that emerge during everyday operation [2]. Recent reviews on machine learning and charging-behavior prediction also indicate that EV charging systems exhibit strong temporal and behavioral heterogeneity, which makes reliability assessment increasingly dependent on data-driven interpretation rather than static engineering assumptions [3]. These developments make failure prediction a central requirement for distributed charging networks rather than a secondary maintenance function.

A second challenge arises from the fact that charger degradation is rarely uniform across a distributed system. Public charging points experience different duty cycles, queue intensity, idle duration, energy throughput, and user-session irregularity, so identical hardware can evolve toward failure at different rates under different local operating conditions [4]. Multistage charging-performance prediction studies further suggest that charger behavior should be interpreted as a dynamic sequence of changing states rather than a single fixed operating condition, especially when performance deterioration accumulates across repeated sessions [5]. Reliability assessment of intermediate charging ports has also shown that station success rate and infrastructure dependability are strongly influenced by port-level failure tendencies and usage-driven stress conditions [6]. The implication is that distributed EV charging reliability must be modeled as a node-varying and time-varying process.

This problem is not solved adequately by descriptive monitoring alone. While monitoring can show whether a charger is currently available or unavailable, reliability-oriented management requires forward-looking estimation of how likely a node is to fail, how rapidly degradation is progressing, and how remaining service stability differs across the network [2]. Machine-learning-based charging analyses suggest that user behavior, charging duration, energy demand, and operational context can all serve as predictive signals when the goal is to infer future system behavior rather than summarize past system states [4]. In distributed charging systems, these predictive signals are especially valuable because failure at one node can shift demand to neighboring nodes, increasing their stress and indirectly accelerating broader reliability decline. Reliability modeling therefore has to connect local degradation with system-level redistribution effects.

The literature already provides useful foundations in charging-behavior learning, charging-performance prediction, port-level reliability assessment, and flexibility forecasting, but these strands are often treated separately. Some studies emphasize usage prediction, while others focus on infrastructure reliability or performance forecasting, leaving a gap in unified frameworks that explicitly connect distributed charger-state variables, failure indicators, and predictive reliability trajectories into one coherent model. This gap matters because reliability planning in distributed EV charging systems increasingly depends on knowing not only where demand is rising, but where failure probability is accumulating. The present article addresses this need by developing a reliability-modeling and failure-prediction framework for distributed EV charging systems with emphasis on node-level degradation, predictive failure behavior, and network-aware reliability interpretation.

2. Methodology

The proposed methodology models a distributed EV charging system as a set of interconnected charging nodes, each characterized by operational state, usage intensity, environmental exposure, session behavior, and evolving failure tendency. The framework begins by treating charging duration, session timing, energy transfer, and temporal service variability as predictive state descriptors, because ensemble-learning studies on charging-duration prediction have shown that these variables carry strong explanatory value for future charging behavior [7]. User-behavior clustering methods have similarly demonstrated that charger demand cannot be interpreted accurately unless heterogeneous usage patterns are separated into statistically meaningful groups [8]. For this reason, each node in the distributed network is represented not only by hardware identity, but also by a behavioral-operational profile that evolves over time. This allows the reliability model to distinguish structurally weak nodes from temporarily stressed but recoverable ones.

At the node level, the methodology defines a reliability state vector consisting of charging frequency, average session duration, cumulative delivered energy, idle-to-active transition rate, interruption count, queue spillover exposure, local communication stability, and recent abnormal operating events. These variables are chosen because they jointly represent physical loading and operational irregularity, which are the two major drivers of practical charger deterioration in distributed systems. Duration-prediction research supports the inclusion of temporally resolved user-session variables, while behavior-clustering studies support grouping nodes according to recurrent usage structure before forecasting is performed [8]. The reliability state vector is updated over rolling time windows so that transient fluctuations are separated from persistent degradation trends. This turns node reliability into a time-varying quantity rather than a static engineering score.

To capture distributed interactions, the framework introduces a network-coupling layer in which the state of each charger is influenced not only by its own usage history but also by neighboring demand redistribution. A Time Colored Petri Net formulation for EV charging-service modeling has shown that multi-node charging behavior can be represented through state transitions, occupancy evolution, and geographically distributed service logic across several charging areas [9]. Building on that logic, the present framework assigns each charger node a local reliability trajectory and a coupling coefficient that measures how strongly incoming spillover demand or nearby outage conditions alter its stress accumulation. This step is essential because a node can remain locally healthy yet experience accelerated deterioration after neighboring charger failures redirect traffic toward it. Distributed reliability is therefore modeled as an interaction process rather than a collection of isolated component lifetimes.

The failure-prediction engine combines statistical reliability scoring with data-driven forecasting. First, a node-specific degradation index is computed from normalized operational stress variables such as session density, interruption frequency, unstable throughput, and repeated overload-related transitions. Second, a temporal forecasting layer projects the future evolution of this degradation index over a defined prediction horizon. LSTM-based charging-demand forecasting studies have shown that temporal learning is effective when charger usage changes through sequential dependence rather than isolated events [10]. Explainable machine-learning work on charging-demand prediction has further supported the use of feature-attribution logic so that forecasted deterioration can be interpreted in terms of dominant operational drivers instead of being treated as a black-box output [11]. The framework therefore predicts not only whether a node may fail, but also why its risk is increasing.

A failure-probability function is then assigned to each node by mapping the predicted degradation trajectory into a bounded risk value over time. This function is not based on a single threshold crossing; instead, it grows according to the interaction between projected stress accumulation and local service stability. Nodes with rising load concentration but stable operating behavior may show gradual risk escalation, while nodes with moderate load and repeated abnormal interruptions may show much faster failure-probability growth. The resulting risk curves are aggregated across the network to estimate distributed service reliability, regional failure concentration, and likely instability clusters. This makes the model suitable for both node-level maintenance planning and system-level reliability supervision.

To improve interpretability, the methodology partitions the distributed charging network into behavioral reliability classes before final prediction is performed. Nodes are grouped into categories such as stable-low-stress, stable-high-utilization, transition-prone, and degradation-sensitive classes based on their rolling state vectors and forecasted stress patterns. This classification prevents one uniform prediction rule from being imposed on chargers that experience very different operating realities. It also makes the model more useful for practical decision-making, because intervention strategies can then be linked to reliability class rather than only to raw risk score. The output of the predictive layer is therefore both numerical and operationally interpretable. The principal reliability variables, failure indicators, and forecasting features used in the proposed distributed EV charging model are summarized in Table 1.

Table 1. Reliability Variables, Failure Indicators, and Prediction Features in the Proposed Distributed EV Charging Model

Variable group	**Representative variables**	**Predictive role**
Usage intensity	session count, average charging duration, cumulative energy throughput	captures load-driven wear and duty-cycle stress
Service irregularity	interruption frequency, failed sessions, queue spillover rate	reflects unstable operation and degraded user-facing continuity
Temporal behavior	rolling demand trend, peak-period recurrence, dwell-time variability	supports sequential failure forecasting
Node interaction	neighboring outage influence, redistributed charging demand, regional occupancy pressure	captures distributed reliability coupling
Stability indicators	communication consistency, power-delivery smoothness, recent abnormal events	identifies early degradation and rising failure tendency

The final evaluation stage measures the model using prediction-centered reliability metrics rather than simple forecasting error alone. The principal outputs are predicted node survival stability, failure-probability growth, degradation-index evolution, and distributed service reliability under changing stress conditions. These outputs allow the framework to estimate where failures are likely to emerge, how rapidly reliability is declining, and which charging nodes contribute most to system-wide vulnerability. The methodology is therefore designed to support reliability-aware operation, predictive maintenance, and distributed failure anticipation across EV charging systems.

3. Results and Discussion

The proposed reliability-modeling framework produced clearly separable reliability trajectories across chargers exposed to different operating stress conditions. Under low-stress distributed operation, the predicted reliability curve declined gradually and remained comparatively stable over the observation horizon, indicating that moderate session density and balanced demand distribution do not accelerate failure accumulation significantly. Under medium-stress conditions, reliability decreased at a faster but still manageable rate, mainly because repeated usage cycles and localized queue pressure increased the degradation index more steadily over time. The most pronounced decline occurred under high-stress and overload-prone scenarios, where cumulative energy throughput, interruption recurrence, and redistributed spillover demand jointly amplified the projected failure tendency. This behavior is illustrated in Figure 1, where the predicted reliability trajectories diverge progressively as charger stress intensity increases. The result shows that reliability in distributed EV charging systems is strongly path-dependent and cannot be represented accurately by a single average failure trend for the whole network.

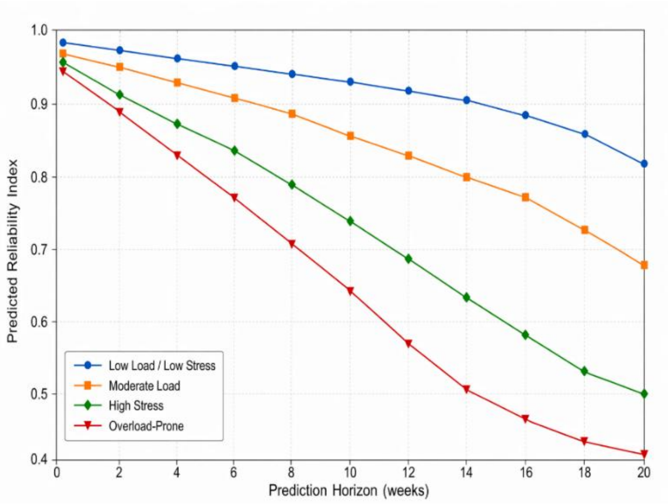

Figure 1. Predicted Reliability Trajectories Under Different Charger Load and Stress Conditions

A second important result concerns the relationship between failure probability growth and remaining service stability at the node level. Chargers that experienced relatively balanced demand and low operational disturbance maintained a slower rise in failure probability and retained a higher level of service stability throughout the prediction horizon. In contrast, chargers exposed to repeated interruptions, unstable throughput, and neighboring demand spillover showed a much sharper increase in failure probability, accompanied by a noticeable decline in projected service continuity. This effect became more visible in nodes classified as degradation-sensitive, where even moderate stress accumulation translated into rapid deterioration of predicted operating stability. This behavior is illustrated in Figure 2, where failure probability increases progressively while remaining service stability declines across distributed charging nodes under different degradation conditions. The results therefore confirm that failure prediction in EV charging systems must capture both intrinsic node stress and inter-node dependency.

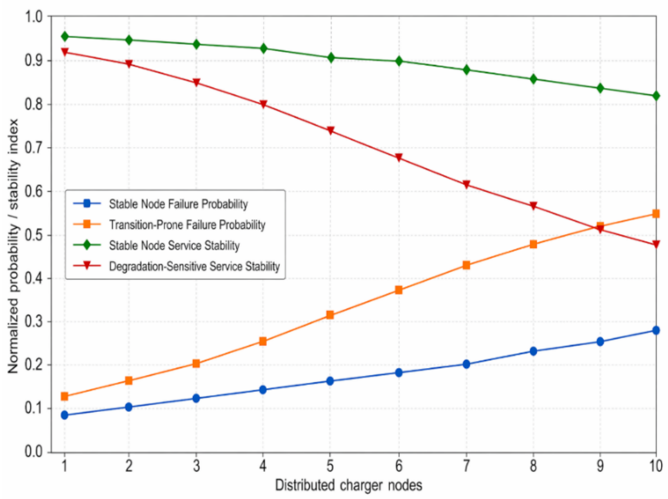

Figure 2. Failure Probability Growth and Remaining Service Stability Across Distributed EV Charging Nodes

The class-based reliability grouping also improved interpretability of the prediction results. Nodes belonging to the stable-low-stress class maintained comparatively flat degradation-index growth and showed only mild reliability reduction over time, while stable-high-utilization nodes displayed higher throughput exposure but still preserved acceptable service stability when interruption frequency remained low. Transition-prone nodes exhibited intermediate behavior, with reliability declining more quickly once local demand volatility began interacting with repeated operational irregularity. The most critical pattern emerged in degradation-sensitive nodes, where the combination of high session turnover, frequent interruptions, and spillover load caused both reliability loss and failure-probability growth to intensify early. This classification outcome is useful because it transforms the prediction framework from a purely numerical forecasting tool into an operational decision aid. Maintenance planning can therefore be prioritized according to reliability class rather than only by raw predicted failure score.

Another notable outcome was the effect of temporal forecasting on early failure awareness. If reliability assessment were based only on current operating condition, several nodes would still appear moderately healthy despite being on steep deterioration trajectories. By projecting degradation-index evolution forward in time, the framework exposed nodes whose present condition was acceptable but whose future reliability decline was likely to accelerate under persistent stress. This makes the model especially valuable for predictive maintenance and distributed asset planning, because interventions can be scheduled before charger instability becomes user-visible or causes secondary stress on neighboring nodes. In practical terms, the forecasting layer shifts reliability management from reactive replacement toward anticipatory control. The system therefore gains operational value not from detecting failure after occurrence, but from estimating where reliability erosion is likely to emerge next.

The network-coupling component also contributed significantly to the realism of the results. In a purely independent-node model, each charger would evolve according to its own historical load and local degradation variables, but the present framework showed that distributed reliability is altered materially when neighboring faults or heavy-demand zones redirect charging activity. Nodes located near stressed or partially degraded chargers accumulated risk more rapidly than their own local history alone would suggest, because redistributed demand increased session density and service irregularity. This interaction effect explains why some chargers moved from stable classes into transition-prone or degradation-sensitive classes during the prediction horizon even without an internal component shock. The result highlights the importance of treating distributed EV charging reliability as a network phenomenon rather than a collection of isolated component forecasts.

4. Conclusion

This study presented a reliability-modeling and failure-prediction framework for distributed EV charging systems with emphasis on node-level degradation, network-coupled stress behavior, and predictive reliability evolution. The proposed approach treated each charger as a dynamic operational entity whose failure tendency depends on usage intensity, service irregularity, temporal demand behavior, and interaction with neighboring nodes. By combining rolling state vectors, degradation-index forecasting, distributed coupling logic, and failure-probability estimation, the framework provided a structured method for anticipating reliability decline before visible service collapse occurs. This makes the model relevant for modern charging networks in which operational variability and distributed dependence strongly influence infrastructure performance.

The results showed that reliability trajectories differ substantially across charger stress classes and that failure probability can grow rapidly when local degradation is reinforced by redistributed demand and service instability. The framework also demonstrated that class-based reliability grouping improves interpretability, while temporal forecasting strengthens early failure awareness and predictive maintenance value. Rather than describing charger reliability as a static property, the study showed that it should be understood as an evolving network-linked process. This is particularly important in distributed charging environments, where local failure can alter the operating burden of neighboring nodes and accelerate broader reliability decline.

The broader implication of this work is that future EV charging systems should incorporate predictive reliability modeling as part of routine operational management rather than relying only on current-state monitoring. Further extensions can include survival-analysis-based hazard estimation, digital-twin-assisted degradation simulation, weather-sensitive reliability forecasting, and federated prediction across geographically distributed charger fleets. Additional study may also explore mixed-vendor charger populations, joint communication-and-hardware failure behavior, and maintenance optimization using predicted reliability classes. These directions would help move distributed EV charging infrastructure toward more proactive, reliable, and failure-aware operation.

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