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Research Article

Enhancing EV Charging Station Reliability and RAS Safety

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The surge in electric vehicle (EV) adoption prompts companies to prioritize dependable charging station designs, despite hurdles in maintaining consistency. A newly proposed design, featuring 36 ports, employs both uniform and non-uniform arrangements and is subjected to rigorous testing with systems ranging from 50 to 350 kW. Failure rates are projected through meticulous assessments based on MILHDBK217F and MILHBK-338B standards, employing binomial distribution and cost analysis to gauge port reliability and overall station success rates. This innovative design not only bolsters voltage stability but also curtails maintenance expenses by enhancing port reliability. In the realm of robotics and autonomous systems (RAS), Deep Reinforcement Learning (DRL) demonstrates exceptional prowess but grapples with the risk of unsafe policies, potentially resulting in perilous decisions. To address this concern, a novel study introduces a reliability evaluation framework tailored for DRL-driven systems, leveraging formal neural network analysis. This framework adopts a two-tiered verification strategy: firstly, by assessing safety locally using reachability tools, and secondly, by aggregating local safety metrics across various tasks to evaluate global safety. Empirical validation confirms the efficacy of this framework in fortifying the safety of RAS.

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Introduction

Increasing awareness of global warming has sparked a heightened interest in electric vehicles (EVs) as environmentally friendly substitutes for traditional automobiles. This shift is primarily motivated by concerns regarding pollution and the depletion of fossil fuel reserves. Governments are actively encouraging the installation of EV charging stations through incentives, presenting a challenge for power system engineers to fulfill demand while upholding grid stability and voltage control. Complicating factors such as land costs and the unpredictability of EV usage further add complexity to the placement of these charging stations. A study [1] evaluates the impact of increasing PEV adoption on distribution network investments and energy losses, indicating potential investment increases of up to 15% and energy losses of up to 40% during off-peak hours with high PEV usage. Probabilistic power flow (PPF) analysis is suggested for managing the uncertainty in Plug-in Hybrid Electric Vehicles (PHEVs) charging demands, incorporating a unique charging model and queuing theory [2][3].

A multi-objective approach [4][5] is proposed for optimizing vehicle-to-grid (V2G) parking lots as distributed generation (DG), considering infrastructure reliability, power losses, and costs. A static EV load model is developed to aid stability analysis, showing that rapid charging impacts grid voltage stability [6][7]. Security and reliability concerns arise from unregulated EV charging, necessitating intelligent scheduling systems [8][9]. Various probabilistic methods [10][11] and optimization approaches [12] are explored to address these challenges, including genetic algorithms and particle swarm optimization. Research [12][13] suggests integrating PEV parking lots to minimize system costs and optimize profits for distribution firms, accounting for EV growth projections [14]. Optimization models [15][16] prioritize charging station cost-efficiency and reliability, analyzing EV owner behaviors.

A scheduling approach [17] for EV charging intervals is introduced to optimize power exchange between parking lots, distribution networks, and EVs. The research emphasizes the importance of strategic decision-making for charging station installations, utilizing genetic algorithms [18] and optimized staging plans [19][20][21]. Despite EVs′ environmental and economic benefits, their integration strains distribution systems with voltage instability, maintenance costs, and reliability issues. Unregulated charging and the stochastic nature of EV charging processes pose additional challenges, requiring careful consideration of location, user concentration, and financial viability for charging station setups. Deep Reinforcement Learning (DRL) has shown promise in various applications but faces safety concerns in real-world, safety-critical contexts like autonomous vehicles and power systems. This work addresses the reliability and robustness issues of DRL and Deep Neural Networks (DNN) in such applications, proposing a two-level verification framework. This framework leverages local reachability analysis and global software reliability engineering principles to ensure the safety and reliability of DRL algorithms.

Deep Reinforcement Learning (DRL) has shown remarkable progress across various sectors, particularly in robotics and autonomous systems. As these technologies permeate our daily lives and critical infrastructures, ensuring their safety and reliability becomes increasingly crucial. While DRL algorithms excel at training decision-making agents to optimize long-term performance, real-world scenarios demand more than just optimal performance; they require robustness, stability, and safety. Consequently, the field of DRL verification and testing has evolved to guarantee system properties across an infinite input space. [22] introduced adversarial attacks tailored for DRL algorithms, enhancing performance and robustness when trained with these engineered attacks [5]. However, relying solely on adversarial training methods falls short in ensuring safety during the training phase. Addressing this gap, we developed a safety layer that computes action corrections per state to maintain safety throughout the training process. Lyapunov functions are applied to define regions of attraction for specific policies and applied statistical models to optimize high-performance DRL policies. Despite advancements in safety during training, discrepancies between training and testing environments persist. To mitigate this risk, run-time monitors, such as the shield structure, were introduced to prohibit agents from executing unsafe actions for each state, thereby ensuring safety during operations.

DRL verification presents multifaceted challenges distinct from traditional Deep Learning (DL) verification. The sequential decision-making inherent to DRL,

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where a Deep Neural Network (DNN) is invoked repeatedly for each action decision, coupled with the often stochastic environments, poses significant scalability challenges. For applications like autonomous vehicles, ensuring consistent actions across both perturbed and unperturbed states at each decision point is essential. To address these challenges, various DRL verification methodologies have emerged, including abstraction, constraint-based verification, reachability analysis, and model checking [12]. Our research primarily focuses on "Reachability Analysis," encompassing notable algorithms.

Despite these advancements, a knowledge gap persists regarding DRL safety. Current methods can detect safety violations under extreme conditions but often fall short in providing a comprehensive understanding of DRL policy safety, especially when violations occur locally. In the context of charging station installations, the capacity is determined by available parking spaces, but this alone isn't sufficient for configuring and installing ports to serve customers effectively. The installation depends on capital investment and expenditure for achieving maximum charging port capacity in a given area. Therefore, before installing a charging station, reliability tests should be conducted on the selected port configuration to allocate budgets for procuring the required ports. Based on this understanding, reliability estimation methodologies are developed to ensure the robustness and effectiveness of the charging infrastructure, aligning with the broader objective of enhancing DRL safety and reliability.

Methodology

To assess the reliability of the charging port arrangement, we initially focus on the uncertain plug-in conditions. Both uniform and non-uniform port designs are examined to accommodate varying plug-in scenarios. Intermediate operating conditions in electric vehicles (EVs) present challenges, with potentially higher failure rates in charging stations due to fluctuating loads on charging ports. The occurrence of failures depends on customer demand, which varies by power ratings. Persistent port failures can disrupt services, making port replacement essential to maintain consistent charging. The quality of the replacement port is crucial and is determined based on material standards aligned with capital investment benchmarks for port maintenance. Therefore, cost estimation is essential to allocate a maintenance budget for procuring quality replacements, enhancing charging facility reliability. Product lifespan is evaluated to verify quality compliance, adhering to MIL-HDBK217F standards. Using this methodology, reliability is estimated in terms of failure rates for each port within the charging arrangement. The charging station's capacity and capabilities hinge on the port configuration and arrangement. While uniform port layouts are popular for EV charging stations, they require more installation space.

Ensuring equal parking space for vehicles presents challenges for charging stations. Despite this, uniform ports typically have simpler and lower maintenance costs compared to non-uniform ports. Non-uniform ports operate across a range of power ratings, making them suitable for compact installations, whereas uniform ports offer longevity, reliability, and easier maintenance. Considering these factors, we evaluate installation efficiency, failure rates, reliability, and maintenance costs for both uniform and non-uniform port configurations. Based on these considerations, we propose a 36-ported charging station structure that combines both uniform and non-uniform port arrangements. To assess the combined configuration of uniform and non-uniform charging ports in the proposed 36-port charging station, we introduce a

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stepwise evaluation approach. The goal is to design a reliable charging station by selecting the appropriate distribution system for installation area, system configuration, and probability method. We opt for the binomial distribution to determine the necessary charging station capacity for 36 ports.

The proposed 36-port station combines both uniform and non-uniform configurations, accommodating various port populations to optimize charging facilities based on parking lot capacities. Reliable charging largely hinges on port reliability in terms of failure rates, which can be influenced by EVs' intermediate charging patterns. Understanding these failure probabilities requires a methodology that can address both real and hypothetical scenarios through statistical validation. To evaluate these hypothetical failure probabilities, we employ probability statistical methods to assess the reliability of each port in the charging station. Our approach uses the binomial distribution due to its applicability to both uniform and non-uniform configurations. The binomial distribution allows for simultaneous comparisons of two distinct probability evaluations, offering accurate insights into the probability and reliability of the proposed 36-port configurations. A charging station with a power range of 50-350 kW serves as our model for this analysis. We follow the prescribed workflow for uniform and non-uniform systems, starting with the selection of 36 ports and incorporating reliability methods. The reliability evaluation considers random EV charging processes across various repetitive combinations.

The charging station features a dual-batch system for parking lot convenience. The uniform system comprises 20 ports, with 2 being susceptible to vulnerabilities. Meanwhile, the non-uniform system offers 16 ports, and we employ a repeatability method to assess product reliability. Repeatability occurs when a random configuration is selected, culminating in a comprehensive assessment of the charging station's failure rates. Ultimately, the system's failure rate is evaluated based on MILHBK-338B standards, incorporating both uniform and non-uniform configurations to ensure a thorough and reliable analysis.

Review of Results

Evaluating the reliability and economics of Electric Vehicle (EV) charging configurations is crucial as the adoption of EVs continues to grow globally. Reliable charging infrastructure is essential to support the widespread use of EVs and to address concerns about range anxiety among consumers. Various factors contribute to the reliability of EV charging systems, including the design of charging ports, the distribution of charging stations, and the maintenance protocols in place. Economic considerations are equally important, as the cost-effectiveness of charging configurations impacts both consumers and service providers. Evaluating these aspects helps to optimize the design and operation of EV charging infrastructure, ensuring its long-term sustainability and affordability.

Deep Reinforcement Learning (DRL) has emerged as a powerful tool in the fields of robotics and autonomous systems, offering promising advancements in decision-making and control algorithms. DRL algorithms enable agents to learn optimal strategies through trial and error, improving performance over time. In robotics and autonomy, the reliability of DRL algorithms is paramount, as incorrect decisions can lead to system failures or safety hazards. Evaluating the reliability of DRL algorithms involves rigorous testing and validation processes to ensure their robustness across various scenarios and environments. Additionally, understanding the economic implications of implementing DRL in

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robotics and autonomy is crucial for cost-effective system development and deployment. Integrating DRL into EV charging configurations presents new opportunities and challenges. DRL algorithms can optimize charging schedules, manage energy storage, and enhance grid integration, leading to more efficient and reliable charging systems. However, implementing DRL in this context requires careful evaluation of its reliability and economic feasibility. Ensuring that DRL algorithms operate safely and efficiently within the complex and dynamic environment of EV charging infrastructure is essential. Moreover, understanding the economic costs and benefits of integrating DRL into EV charging systems helps stakeholders make informed decisions about investment, development, and deployment strategies.

Significance of Results

Evaluating the reliability and economics of EV charging configurations and DRL in robotics and autonomy is essential for advancing these technologies and ensuring their successful integration into modern transportation and energy systems. Comprehensive assessments that consider both technical and economic factors enable stakeholders to make informed decisions, optimize system designs, and address challenges effectively. As EV adoption and automation continue to accelerate, ongoing research and evaluation efforts will play a critical role in driving innovation, enhancing reliability, and achieving sustainable and cost-effective solutions for future mobility and energy infrastructure.

Conclusion

This study underscores the importance of reliable charging station designs in meeting the growing demand for Electric Vehicles (EVs). The proposed 36-ported design, integrating both uniform and non-uniform port arrangements, offers a promising solution to enhance port reliability and reduce maintenance costs, particularly for systems ranging from 50-350 kW. By leveraging established standards like MILHDBK217F and MILHBK-338B, along with binomial distribution and cost analysis, the design demonstrates improved voltage stability and a more sustainable charging infrastructure. Furthermore, in the realm of robotics and autonomous systems (RAS), the study addresses critical challenges associated with the deployment of Deep Reinforcement Learning (DRL) algorithms. While DRL has shown significant promise in enhancing RAS performance, concerns about safety and reliability persist due to potential hazardous decisions stemming from unsafe policies. This research introduces a comprehensive reliability assessment framework for DRL-controlled systems, leveraging formal neural network analysis and a two-level verification approach. By assessing safety both locally and globally, the framework offers a robust methodology to evaluate and enhance the safety of DRL-driven RAS.

Overall, the findings from this study provide valuable insights and methodologies for advancing both EV charging infrastructure and DRL-controlled RAS. By focusing on reliability, safety, and cost-effectiveness, the research contributes to the development of more resilient and efficient systems, addressing key challenges and paving the way for broader adoption of EVs and autonomous technologies in the future.

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Statements and Declarations

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request. The analysis relies on methodologies derived from MIL-HDBK-217F, MIL-HDBK-338B standards, and computational simulations.

Ethics

Ethical review and approval were not required for this study in accordance with local legislation and institutional requirements, as the analysis relied solely on simulations, publicly available standards, and existing literature. No new data involving human participants or animals were collected.

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Declarations

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