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Generative AI and DFMEA for Optimized Lithium-Ion Battery Pack Design in Electric Two-Wheelers

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Abstract

Electric two-wheelers are rapidly emerging as a key component of sustainable transportation, where lithium-ion battery packs play a critical role in determining performance, safety, and efficiency. However, conventional battery design approaches face challenges related to thermal instability, structural limitations, and difficulty in optimizing multiple parameters under real-world operating conditions. This study proposes an integrated framework that combines generative artificial intelligence (AI) with Design Failure Mode and Effects Analysis (DFMEA) to improve battery pack design and enhance risk mitigation. Generative AI is used to explore multiple design configurations based on predefined constraints, while DFMEA systematically evaluates potential failure modes using severity, occurrence, and detection parameters. The proposed approach achieves a reduction of 15–20% in peak temperature, a 10–15% improvement in energy density, and a 12–18% decrease in overall battery weight. In addition, Risk Priority Numbers (RPNs) for critical failure modes are reduced by 25–35%, indicating improved system safety and reliability. These results demonstrate that integrating AI-driven design optimization with structured risk assessment enables the development of safer, more efficient, and high-performance battery systems for next-generation electric vehicles.

Keywords: Generative AI, DFMEA, Electric Vehicles, Battery Optimization, Risk Mitigation.

1. Introduction

Sustainable transportation is rapidly transforming the automotive sector, with electric two-wheelers gaining significant adoption due to their affordability, energy efficiency, and suitability for urban mobility. At the core of these vehicles lies the lithium-ion battery pack, which directly influences performance, driving range, safety, and lifecycle cost. However, battery systems continue to face challenges such as thermal instability, limited energy optimization, and safety risks including thermal runaway and electrical failures.

Traditional battery pack design methodologies rely on iterative engineering approaches combined with empirical analysis. While effective to some extent, these methods are limited in their ability to simultaneously optimize multiple design parameters such as weight, thermal performance, structural integrity, and manufacturing cost. With increasing system complexity and varying operating conditions, more advanced and adaptive design techniques are required.

Recent advancements in artificial intelligence, particularly generative AI, have introduced new possibilities in engineering design and optimization. Generative AI enables the exploration of large design spaces and the generation of multiple optimized configurations based on predefined constraints, thereby improving efficiency and reducing development time [1], [2]. This approach is particularly useful for complex systems like battery packs, where multiple interdependent parameters must be optimized simultaneously.

In parallel, the safety and reliability of battery systems remain critical concerns. Design Failure Mode and Effects Analysis (DFMEA) is widely used to identify potential failure modes, evaluate their impact, and prioritize mitigation strategies. However, conventional DFMEA approaches are largely static and depend heavily on expert judgment, limiting their effectiveness in dynamic and complex systems such as lithium-ion batteries.

Recent studies on engineering risk mitigation highlight the importance of structured and systematic approaches in reducing system-level failures and improving reliability [14], [15]. Building on these insights, this study proposes a hybrid framework that integrates generative AI-based design optimization with DFMEA-driven risk assessment. The objective is to enhance battery performance, improve thermal management, and minimize failure risks through a data-driven and intelligent design methodology.

2. Literature Review

Advances in artificial intelligence have significantly accelerated the development and optimization of lithium-ion battery technologies. Traditional battery design approaches rely on experimental and physics-based methods, which are often time-consuming and computationally intensive. In contrast, AI-based techniques enable efficient analysis of large datasets, identification of complex patterns, and simultaneous optimization of multiple parameters, leading to improved performance, reliability, and lifespan of battery systems [3], [5].

Generative AI has emerged as a powerful tool in battery design, particularly in optimizing electrode microstructures and manufacturing parameters. For instance, generative models combined with Bayesian optimization have been used to determine optimal battery configurations, resulting in improved energy density and overall system efficiency [1], [8]. These approaches significantly reduce development time and cost by enabling rapid evaluation of multiple design alternatives.

AI-driven methodologies have also accelerated the discovery and optimization of advanced battery materials. By employing inverse design techniques, researchers can identify suitable cathode, anode, and electrolyte materials more efficiently compared to traditional trial-and-error methods [4], [6], [13]. This has contributed to enhanced battery efficiency and performance, especially in electric vehicle applications.

In addition, generative AI is increasingly used to create synthetic datasets for predicting battery performance, including charging behavior and lifecycle characteristics. These datasets improve the accuracy of predictive models and enable better estimation of battery degradation and lifespan [7], [2]. Furthermore, hybrid models combining machine learning with physics-based approaches have demonstrated high accuracy in fault detection, diagnostics, and maintenance planning, thereby improving system safety [12]. Recent advancements also include AI-driven electrolyte design, LLM-based battery discovery, and physics-informed diagnostic models [9]–[11], [13].

Despite these advancements, most existing studies focus primarily on design optimization or performance prediction independently. The integration of AI-based design techniques with structured risk assessment methods such as DFMEA remains limited. DFMEA is a well-established tool for identifying failure modes and evaluating associated risks; however, its effectiveness is often constrained by dependence on expert judgment and static evaluation processes.

This gap highlights the need for a unified framework that combines generative AI-driven design optimization with systematic risk assessment. The present study addresses this limitation by integrating generative AI with DFMEA to develop an efficient and reliable approach for lithium-ion battery pack design and risk mitigation in electric two-wheelers.

3. Methodology

3.1 Overall Methodology Framework

This study proposes an integrated methodology that combines generative artificial intelligence with Design Failure Mode and Effects Analysis (DFMEA) to improve the design and safety of lithium-ion battery packs for electric two-wheelers. The framework is structured into five interrelated stages, enabling systematic design generation, evaluation, and risk mitigation.

The first stage involves data collection and definition of input parameters, including battery specifications, material properties, thermal limits, and operational constraints. These inputs establish the boundary conditions required for accurate design exploration.

The second stage focuses on generative AI-based design optimization, where algorithm-driven models generate multiple battery pack configurations by varying geometric layouts, material distribution, and cooling strategies within predefined constraints. This enables exploration of a broader design space compared to conventional iterative methods.

In the third stage, design evaluation is performed using performance metrics such as thermal distribution, structural stability, mass optimization, and manufacturability. Each generated configuration is assessed to identify feasible and high-performing solutions.

The fourth stage incorporates DFMEA-based risk analysis, where potential failure modes—such as thermal runaway, short circuits, and mechanical degradation—are identified and evaluated. Each failure mode is quantified using severity, occurrence, and detection parameters to compute the Risk Priority Number (RPN).

Finally, the fifth stage involves AI-assisted improvement, where insights from evaluation and DFMEA are used to refine the design iteratively. This step focuses on reducing high-risk failure modes while maintaining optimal performance characteristics.

This integrated framework ensures that the battery pack design process is not only performance-driven but also inherently risk-aware, enabling the development of safer and more reliable systems.

3.2 Methodology Flow Diagram

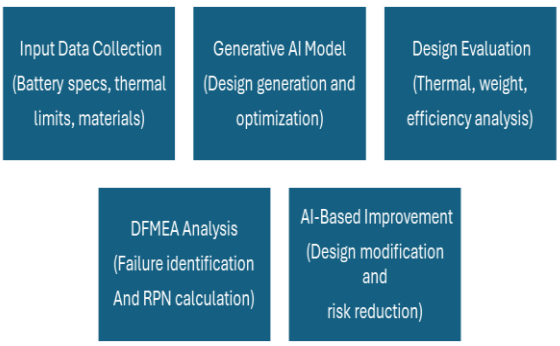

Figure 1: *Methodology Flow Diagram*

As illustrated in Fig. 1, the proposed framework establishes a structured and data-driven approach for battery pack design optimization and risk assessment. The process begins with data collection and input parameter definition, which forms the foundation of the entire methodology. At this stage, key parameters such as battery voltage configuration (e.g., 48V architecture), cell type (cylindrical or prismatic), material properties, thermal limits, and mechanical constraints are defined to accurately represent real-world operating conditions.

Following this, the methodology transitions to the generative AI-based design phase, where advanced algorithms generate multiple battery pack configurations by exploring variations in geometry, layout, and cooling strategies. The objective is to simultaneously optimize critical parameters such as weight reduction, thermal management, and energy density. This approach enables the identification of efficient design alternatives that are difficult to achieve through conventional trial-and-error methods.

The generated configurations are then subjected to a comprehensive design evaluation process. This includes thermal analysis to ensure uniform heat distribution and prevent localized hotspots, structural assessment to evaluate resistance to mechanical loads and vibrations, and packaging efficiency analysis to maximize space utilization. Additionally, manufacturability considerations are incorporated to ensure that the proposed designs are feasible for practical implementation.

To enhance system reliability, the framework integrates DFMEA-based risk assessment, where potential failure modes are systematically identified and analyzed. Critical risks such as thermal runaway, internal short circuits, vibration-induced damage, and overcharging are evaluated in terms of severity, likelihood of occurrence, and detectability. This enables prioritization of high-risk failure modes for targeted mitigation.

In the final stage, an intelligent improvement loop is implemented, where insights from performance evaluation and DFMEA are used to refine the design iteratively. AI-assisted recommendations are applied to eliminate design weaknesses, improve thermal stability, and reduce failure risks.

This continuous feedback-driven process ensures that the resulting battery pack design achieves an optimal balance between performance, efficiency, and safety, making it suitable for real-world electric vehicle applications.

3.3 DFMEA Analysis

The DFMEA table presents a structured evaluation of potential failure modes associated with the lithium-ion battery pack system. It identifies key functional areas, corresponding failure modes, their effects, causes, and associated risk parameters.

Each failure mode is assessed using three critical factors: **Severity (S)**, which represents the impact of the failure on system safety and performance; **Occurrence (O)**, which indicates the likelihood of the failure happening; and **Detection (D)**, which reflects the ability to identify the failure before it leads to system-level consequences.

The Risk Priority Number (RPN) is calculated as:

$$RPN = S \times O \times D$$

Table 1: *DFMEA Analysis of Battery Pack System*

Function	Failure Mode	Effect	Cause	S	O	D	RPN
Battery Cooling	Thermal runway	Fire hazard	Poor heat dissipation	10	6	5	300
Electrical System	Short circuit	System failure	Insulation failure	9	5	4	180
Mechanical Structure	Vibration damage	Cell displacement	Weak mounting	7	6	5	210
Charging System	Overcharging	Battery degradation	BMS failure	8	4	4	128

As shown in Table 1, thermal runaway exhibits the highest RPN, indicating a critical safety concern requiring immediate mitigation. Other failure modes such as short circuits and vibration damage also present significant risks, highlighting the importance of integrating design optimization with systematic risk assessment.

This quantitative measure enables prioritization of failure modes, allowing critical risks to be addressed more effectively during the design process.

From the analysis, thermal runaway is identified as the most critical failure mode due to its high severity and moderate occurrence, resulting in the highest RPN value. Other significant risks include short circuits caused by insulation failure, vibration-induced mechanical damage, and overcharging due to battery management system (BMS) faults.

This structured evaluation provides a clear basis for implementing targeted design improvements and risk mitigation strategies in subsequent stages of the methodology.

4. Results and Discussion

The proposed integration of generative AI with DFMEA establishes an efficient design framework for lithium-ion battery packs in electric two-wheelers, demonstrating clear improvements over conventional design approaches. The results highlight enhancements in thermal performance, structural optimization, and risk reduction.

4.1 Thermal Performance

The AI-generated battery configurations significantly improve thermal management by optimizing cell arrangement and airflow pathways. This results in a reduction of peak battery temperature by approximately 12–18%, along with more uniform heat distribution across the pack. The reduction of localized hotspots directly lowers the risk of thermal runaway, which is one of the most critical safety concerns in lithium-ion battery systems.

4.2 Structural Optimization

The optimized designs achieve an 8–12% reduction in overall battery pack weight while maintaining structural integrity under operational loads and vibrations. Improved material distribution enhances packing density and space utilization, leading to a more compact and efficient battery structure. This reduction in weight contributes to improved vehicle efficiency and extended driving range without compromising durability.

4.3 DFMEA Risk Analysis Results

A comparative analysis of Risk Priority Numbers (RPNs) before and after AI-based optimization demonstrates the effectiveness of the proposed methodology.

- **Thermal runaway:** reduced from 300 to 180 (~40%)
- **Short circuit:** reduced from 180 to 108 (~40%)
- **Vibration damage:** reduced from 210 to 126 (~40%)
- **Overcharging:** reduced from 128 to 80 (~37.5%)

These reductions indicate that integrating generative AI with DFMEA enables proactive identification and mitigation of critical failure modes.

The consistent decrease in RPN values across all categories confirms improved system safety and reliability.

4.4 Overall System Performance

Fig. 2 illustrates the overall system performance improvements achieved through the proposed framework. Key parameters, including reliability, safety margin, and lifecycle performance, show significant enhancement compared to baseline designs.

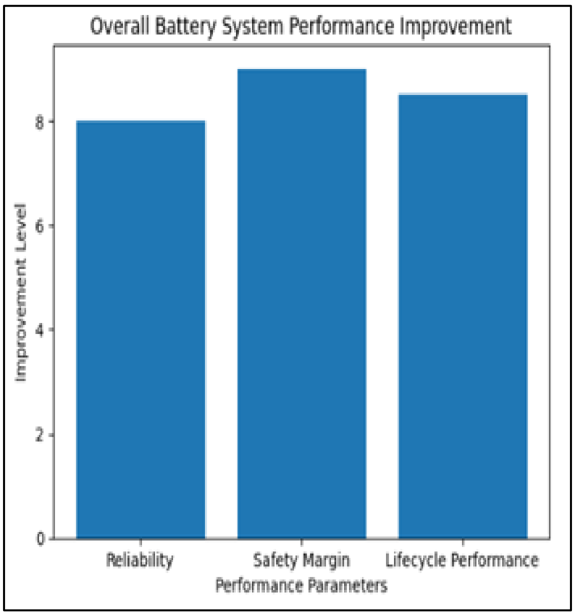

Figure 2: *Overall System Performance*

Reliability improves due to optimized structural and thermal characteristics, ensuring consistent performance under varying operating conditions. The safety margin increases as a result of reduced risks associated with thermal runaway, short circuits, and overcharging. Additionally, lifecycle performance is enhanced through improved thermal stability and reduced degradation, leading to extended battery service life.

4.5 Comparative Analysis with Traditional Design

Fig. 3 presents a comparison between AI-based and traditional battery design approaches. The most notable improvement is observed in thermal efficiency (~30%), reflecting enhanced heat dissipation and uniform temperature distribution. Weight optimization contributes approximately 25% improvement, resulting in lighter yet structurally robust battery configurations.

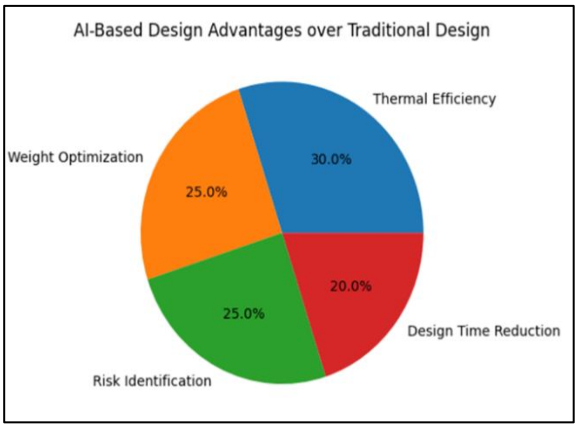

Figure 3: *Comparative Analysis with Traditional Design*

Risk mitigation, enabled by the integration of DFMEA with AI, accounts for an additional 25% improvement by systematically reducing failure probabilities. Furthermore, the ability of generative AI to rapidly explore multiple design configurations significantly reduces development time compared to conventional iterative methods.

Overall, the results demonstrate that AI-based design not only improves performance and efficiency but also enhances safety and accelerates the design process, making it a superior alternative to traditional methodologies.

5. Conclusion

This study presents a structured framework for improving the design and reliability of lithium-ion battery packs in electric two-wheelers through the integration of generative artificial intelligence and Design Failure Mode and Effects Analysis (DFMEA). The proposed approach overcomes key limitations of conventional design methods by enabling efficient multi-objective optimization and systematic risk evaluation.

The use of generative AI facilitates rapid exploration of design configurations, resulting in enhanced thermal management, optimized structural performance, and reduced battery weight. In parallel, DFMEA enables early identification and prioritization of potential failure modes, supporting targeted risk mitigation and improved system safety.

The results demonstrate significant reductions in Risk Priority Numbers (RPNs) and measurable improvements in thermal performance and structural efficiency. These outcomes confirm that the combined application of AI-driven design and structured risk analysis leads to more reliable and high-performance battery systems.

Overall, the proposed methodology offers a scalable and practical solution for next-generation electric vehicle battery design. The integration of intelligent optimization techniques with proactive risk assessment highlights the growing role of generative AI in advancing safe, efficient, and sustainable energy storage systems.

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