Proceedings of the 35th European Safety and Reliability & the 33rd Society for Risk Analysis Europe Conference
Edited by Eirik Bjorheim Abrahamsen, Terje Aven, Frederic Bouder, Roger Flage, Marja Ylönen
 Published by Research Publishing, Singapore.
doi: 10.3850/978-981-94-3281-3_ESREL-SRA-E2025-P3853-cd

Failure Mode and Effects Analysis for a Battery Storage System Using Second Life Lithium-Ion Batteries

Hector Hernandez

Department of Systems Engineering, Colorado State University, USA. hector.hernandezramirez@colostate.edu

Vincent Philip Paglioni

Department of Systems Engineering, Colorado State University, USA. Vincent.Paglioni@colostate.edu

Abstract

It is well known that Lithium-Ion (Li-ion) batteries are one of the most common tools for storing energy due to their versatility and scalability. With the growth of the electric vehicle market, the relatively short life of Li-ion batteries in vehicle service could lead to significant battery waste. To address this issue, methods have been developed to recycle these components and give them a second use in complex electrical systems, contributing to the fight against climate change. However, if not properly treated, failures in Li-ion batteries can present risks to human health and the environment. Therefore, reliable systems are needed for the use of Li-ion batteries, especially in critical energy storage applications. Several aspects must be considered when assessing the reliability of a system, some of them include evaluating the failure modes of system components and determining how these failures may impact the entire system. A specific method used throughout all stages of this process is Failure Mode and Effect Analysis (FMEA). Although this is methodical and time-consuming, FMEA helps identify the causes of events that lead to system failure determining the consequences, and ultimately, minimizing both the occurrences and recurrences of such events. For this work, a system based on recycled Li-ion batteries for energy storage purposes was evaluated using FMEA. This reliability analysis comprehensively assessed risks represented by each of the components leading to the identification of the dependence between sensors, tools for temperature regulation, and control methodologies (voltage, current, and cycles), which contribute to creating a suitable environment for the use of batteries in energy storage. Failures related to these components can lead to capacity and power fade issues, which, if they progress, can result in total system loss or may pose serious threats to human health and to the environment.

Keywords: Li-Ion Batteries, Risks, Failures, Reliability, Energy Storage, Failure Modes

1. Introduction

In today's world, most human activities that require energy (electricity) rely on the usage of fossil fuels. In May 2024, roughly 55% of net generation capacity in the U.S. was derived from coal, petroleum, or natural gas (U.S. Energy Information Administration 2024). The burning of these fuels not only harms human health but also has significant environmental impacts (e.g., the release of pollutants, greenhouse gases, and the rapid depletion of fossil fuel reserves) serving as a major contributor to global climate change (Prasad et al. 2024).

The issues associated with fossil fuel use are coming to bear coincidentally with a steep rise in energy demand, driven by increasing development and new, power-hungry technologies such as Artificial Intelligence (AI) (Goldman Sachs 2024). With the rapid development of industry and the push for a sustainable, environmentally friendly economy, the drive to meet these demands has led to increasingly complex clean energy solutions (Fan et al. 2020).

The variability of renewable sources (e.g., wind and solar) make them insufficient to provide power to large-scale electrical grids. Combining these technologies with Battery Energy Storage Systems (BESS) reduces intermittency and unpredictability. By storing excess energy during low-demand periods and releasing it during peak demand, BESSs improve energy resilience by supplying backup power during grid disruptions or crises, alleviating grid stress, and reducing the need for costly infrastructure (N. Guru et al. 2024).

Electric Vehicles (EVs) are rapidly decarbonizing the transportation sector, and using recycled EV components in other applications can reduce end-of-life waste and contribute to decarbonizing other industries (Martinez-Laserna et al. 2018). One of these components is lithium-ion batteries (LIBs), which retain 70–80% of their initial capacity when retired from EV use (Martinez-Laserna et al. 2018). These batteries can then provide energy storage services in less demanding applications such as stationary BESSs (Faessler 2021), due to their high energy efficiency and power density.

However, BESSs are not without risks. BESS installations that incorporate physical and chemical safety mechanisms, along with control-base algorithms, have been associated with various risks related to their use (e.g., premature shutdowns, fires, and system damage leading to cascading effects), often resulting from short circuits caused by overloading, overheating, or mechanical abuse (Conzen et al. 2023).

Regardless of BESS application, an unplanned shutdown could result widespread consequences: from loss of power to critical infrastructure, to grid instability, and/or damage to other generation equipment. Furthermore, the system design and lack of operational experience could introduce potentially unknown risks when using these systems.

To identify and prevent the risks associated with these types of systems, Failure Mode and Effects Analysis (FMEA) is used to conduct early-stage risk assessments. This approach offers several advantages throughout product development, enabling the identification and resolution of potential risks before they escalate into costly problems (Sharma and Srivastava 2018), facilitating the development of countermeasures to mitigate potential failures.

In this paper, a comprehensive Failure Mode and Effect Analysis methodology is applied to a BESS with second-life Li-ion batteries to identify failure modes, effects, and causes. The analysis is combined with the use of an online tool, the Reliability Online Automated Databook System (ROADS) (Quanterion Solutions Incorporated 2024), to provide data on the types and probabilities of component failures and their corresponding failure modes. This approach supports risk assessment for the most critical system components identified based on the severity of their occurrence.

2. FMEA and FMECA

Different methodologies are available for conducting system reliability analysis, each offering unique advantages for obtaining results and assessing risks. These methodologies allow for the demonstration of how the functional structure of system components impacts overall system performance, the development of logic-driven approaches for modeling complex systems, and the qualitative and quantitative identification of potential failure modes and their consequences on the system.

Understanding the root causes and mechanisms underlying BESS failures can help design new safety measures and advanced monitoring techniques to detect and prevent potential problems before they occur. FMEA is a key initial step in studying system reliability. By integrating quality and reliability into the design process from the start of a project, FMEA ensures potential issues are mitigated before they occur.

2.1 *Failure Mode & Effects Analysis*

Failure Mode and Effects Analysis (FMEA) was first introduced and developed by the United States Military in the late 1940s (Sharma and Srivastava 2018). FMEA has been widely adopted in, e.g., renewable energy systems, aerospace engineering, automotive manufacturing, and healthcare devices. Its main purpose is to avoid the possibility that a new design, process, or system fails to achieve the intended requirements under specified operating conditions (Sharma and Srivastava 2018). Beyond failure identification, FMEA also (Aerospace Recommended Practice 2020):

- Enhances system safety
- Assesses the impact of critical and/or undetectable failures on the mission.
- Influences the design to mitigate the impact of failures on the final product
- Assists design engineers in selecting a design with a high likelihood of operational success
- Provides data for developing effective maintenance support

The implementation of FMEA involves key steps and concepts (“Concepts - Cameo Safety and

Reliability Analyzer 19.0 LTR - No Magic Documentation," 2024) essential for its proper application. Figure 1 shows the FMEA flow followed in this work.

The main elements of FMEA include:

- **Failure Mode** – A potential way in which a component, subsystem, or system may fail to perform or deliver its intended function.
- **Effect of Failure** – The impact of the failure mode on the intended function.
- **Cause of Failure** – The factors within the design process that might allow the failure to occur, typically expressed in terms of variables that can be corrected or controlled.
- **Severity** – The degree to which the failure impacts system functionality.
- **Occurrence** – The likelihood of the failure occurring.
- **Detection** – The ability to detect the failure before it affects the system.

FMECA (Failure Modes, Effects, and Criticality Analysis) provides a more quantitative approach than FMEA by using failure rate and failure mode rate in place of the occurrence rating. In either case, however, the true power of FMEA is the qualitative information about system and component failures. Understanding the failure mechanisms of lithium-ion batteries (LIBs) within BESSs is essential for evaluating potential products obtained from recycling and second-life applications, developing processes for their reuse, and assessing their effects on environmental impacts (Huang et al. 2018). This necessitates a thorough investigation of the possible paths to failure, rooted in a deep understanding of common degradation processes and failure modes in LIBs and their components (Hendricks et al. 2015).

3. Second Life Li-Ion Batteries in BESS

LIBs show great promise for energy storage applications that can stabilize the energy grid while reducing CO_2 emissions and other environmentally harmful pollutants (Fan et al. 2020). However, the high market cost of new LIBs limits widespread adoption. A promising solution is the reconditioning of LIBs (X. Hu et al. 2022), which extends their useful life by repurposing them for applications with lower power density requirements.

LIBs that no longer meet the requirements of electric vehicles (EVs) can be favorably reused for other applications, e.g., EV charging stations, photovoltaic (PV) systems, frequency regulation grid services, and on-grid or off-grid storage for renewable energy (Coron et al. 2020)). However, concerns remain about whether these reused batteries can consistently meet performance requirements over time, as they degrade due to a large number of physical and chemical mechanisms, as well as exposure to environmental conditions (Birkl et al. 2017).

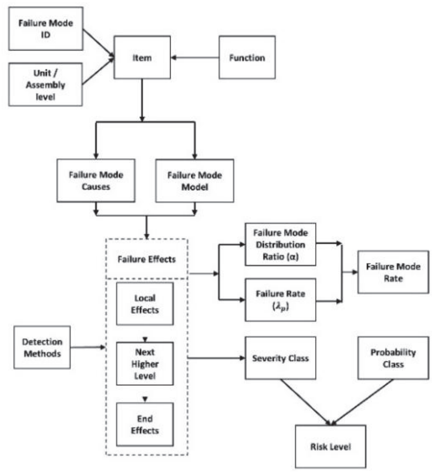

Figure 1. FMEA flow process used in this work.

The reconditioning process may restore some performance characteristics but cannot fully reverse structural and chemical wear, leading to potential failure modes (Shahjalal et al. 2022). Solide-electrolyte interphase (SEI) growth increases impedance, consumes lithium, and reduces conductivity (Birkl et al. 2017). Lithium plating and dendrite formation, which can cause failures related to electrical shorts in the anode/electrolyte zone, occur at low temperatures or when excessive lithiation takes place (Liu et al. 2016) (O'Kane et al. 2022). Poor management of charge currents, combined with high temperatures, can cause electrode particle cracking, potentially leading to physical damage (e.g., internal fractures) (Shahjalal et al. 2022). Additionally, corrosion of current collectors degrades the positive electrode, reducing cathode efficiency, increasing resistance, contaminating electrolytes, and accelerating self-discharge, ultimately resulting in functional failures or degraded battery operation (Gabryelczyk et al. 2021).

These degradation mechanisms directly contribute to the aging of Li-ion batteries, which is typically characterized by capacity loss and an increase in internal resistance (X. Hu et al. 2022). Capacity loss decreases the total energy the battery can store and release, while increased resistance reduces its power output. Both phenomena are primarily driven by the loss of lithium-ion inventory (LLI) and the degradation of anode and cathode active materials (LAM). The degradation process involves various internal aging mechanisms (X. Hu et al. 2022), including side reactions within the battery.

Reconditioning Li-ion batteries for second-life applications presents several challenges, including the safe dismantling of battery packs, the complexities of recycling or repurposing components, and the accurate assessment of battery health through various inspections and model-based testing. Additionally, reassembling components into new battery products for stationary applications requires careful consideration of power capability, energy capacity, service life, and depth of discharge (DOD) (X. Hu et al. 2022). Despite these challenges, BESS present a significant opportunity for their use, as they can play an important role in grids, emergency power supply, telecommunications (G. Lacey, G. Putrus, and A. Salim 2013) (X. Hu et al. 2022), and other applications.

Combining BESS with second-life batteries can reduce the global environmental footprint while offering cost-effective energy storage alternatives (Steckel, Kendall, and Ambrose 2021). Ongoing research and development efforts aim to enhance the performance and reliability of BESS incorporating second-life lithium-ion batteries. Current studies focus on understanding and mitigating degradation mechanisms, optimizing clustering algorithms for battery pairing, and developing innovative thermal management systems.

4. Failure Mode & Effect Analysis on BESS

To conduct the FMEA for the Battery Energy Storage System (BESS), several steps were followed, as described in (Aerospace Recommended Practice 2020). The process consists of defining the system under analysis, which involves dividing the system into its constituent parts using block diagrams to establish the Unit/Assembly (Subsystem) level. This approach ensures alignment with the system's hierarchy, enabling a structured and systematic collection of data (Aerospace Recommended Practice 2020). By breaking the system into subsystems or units, the FMEA process can focus on smaller, more manageable components rather than attempting to analyze the entire system at once. After the subsystems are identified, the components within each subsystem are prioritized and assessed. This requires a clear understanding of the specific functions performed by each component. Understanding these functions allows for the identification of potential failure modes, their causes, and their effects at different levels within the system.

Table 1. Military/Government Severity Ranking Criteria table defining each level of severity (Aerospace Recommended Practice 2020)

SEVERITY CLASSIFICATION		
Category	Level	Description
1	Catastrophic	A failure which can cause death or system loss.
2	Critical	A failure which can cause severe injury, major property damage, or major system damage which will result in mission loss.
3	Marginal	A failure which may cause minor injury, minor property damage, or minor systems damage which will result in delay/loss of availability or mission degradation.
4	Minor	A failure not serious enough to cause injury, property damage, or system damage but which will result in unscheduled maintenance/repair.

The process of populating failure mode information can be approached in various ways, such as leveraging experience with failures in the same or similar systems, or incorporating generic part failure rate data. For this work, the Reliability Online Automated Databook System (ROADS) was used to provide failure rate data for common components (Quanterion Solutions Incorporated 2024). The failure modes described in this tool, combined with failures identified through experience, were the basis for determining the potential effects within the system if any of these components failed.

With the identification of the causes, effects, and failure modes of the components, the risk associated with occurrence is developed as the convolution of probability and consequence severity. Severity is defined as a measure of the impact of a failure mode on the system, mission or application (Aerospace Recommended Practice 2020). The Military/Government Severity Ranking Criteria (Table 1), as described in (Aerospace Recommended Practice 2020), were used in this work.

The second aspect of risk involves calculating the probability that a specific failure mode occurs in a component. To approximate this value, the Failure Mode Rate (λ), also known as the Failure Mode Criticality Number (Cm), is commonly used. It is calculated using the following formula:

$$\lambda = \alpha\beta t\lambda_p \qquad (1)$$

Where:

- λ_p $(Failure\ Rate)$ = the failure rate for all failure modes of a specific component.
- α (Failure Mode Ratio) = the fraction of component failures corresponding to the failure mode (the probability that the item fails in the identified failure mode).
- β (Failure Effect Probability) = the conditional probability that the failure effect with the specified criticality classification will occur, given that the failure mode occurs.
- t (Operation time) = the operating time in hours or the number of operating cycles.

As mentioned above, using ROADS facilitates the acquisition of some parameters required for calculating the Failure Mode Rate. This tool provides data to determine α by calculating the probability of specific failure modes occurring in a component. In addition, λ_p can be obtained by dividing the number of failed units provided by the tool by the total number of tested hours.

For this study, the Failure Effect Probability and Operation Time are both considered equal to 1, with β interpreted as the actual loss of the unit and t as a normalized operational duration. Once the value of λ is obtained, it is used to classify each potential failure mode of an element into categories (Low, Medium-Low, Medium-High, and High) based on the probabilities obtained of the failure mode occurring and the consequences of its effect. The final step is to determine the risk level of the component. This is achieved by comparing the values obtained for the severity class and λ.

The Failure Modes and Causes, Item Failure Rate, and Failure Mode Distribution Ratio columns for each component were obtained from the ROADS datasets. If the specific component could not be found in the dataset, one with similar specifications was used to calculate the Failure Mode Rate. The Failure Effects for each component were categorized into three levels:

- **Local Effect:** Describes the immediate effect of the component failure.
- **Next Higher Level:** Identifies the subsequent level of effects within the system if the failure addressed in time.
- **End Effect:** Highlights the lastly impacts on the system.

The chain of effects outlined in the Failure Effects section is used to determine the severity class, where the end effects serve as the reference for assigning the final severity value in this column. Finally, the combination of the Severity Class values with the Failure Mode Rate is used to evaluate the risk level of failure for each component within the system (1 for high, 2 for medium-high, 3 for medium-low and 4 for low risks).

5. Results

The results obtained from performing the FMEA are presented in 2. Due to the number of components in a complex system such as the BESS, Table 2 only displays the subset of components contributing to the highest risk.

As shown in Table 2, the components contributing the most to system risk are not the LIBs, but rather the the chillers, Battery Management System (BMS) controller, and sensors.

Table 22. FMEA results showing the highest-risk components.

			Failure Effects					
Failure Mode ID	**Item**	**Failure Modes & Causes**	**Local Effects**	**Next Higher Level**	**End Effects**	**Sev. Class**	**Prob. Class**	**Risk Level**
4.11	Fire Sensor – H2	Functional Failure	Unable to detect H_2 inside cabinet	Fire / Explosion	Loss of System; Threat to human	1	Med - High	1
4.21	Fire Sensor – Smoke	Shorted	Unable to detect smoke in battery cabinet	Fire propagation inside the battery cabinet	Loss of system; Threat to human health	1	High	1
4.91	High Voltage Interlock Loop (HVIL)	Improper Output	System operates in unsafe condition	Short circuits; Unsafe electrical environment	Personnel injury; Uncontrolled operation; Unsafe shutdown	2	Med - High	2
5.21	Chiller	Leakage	Loss of coolant, reducing heat dissipation	Water intrusion in cabinet; short circuit; Reduced performance	Increased battery temperature, possible fire in the system	1	Med - High	1
5.22	Chiller	Failed to Operate	Improper temperature regulation; increase in cabinet temperature	Increased temperature in cells; Increase of LLI and LAM in affected batteries;	Capacity fade and power fade in affected batteries; Potential fire in the cabinet	1	Med - High	1
6.21	BMS Controller	Improper Output	Fails to manage SOC; Incorrect management of temp.	Improper Charging / Discharging cycles leading to overheating	High increase of Capacity and Power fade on affected batteries	2	Med - High	2
6.23	BMS Controller	Electrical Failure	Unsafe system operation	Unsafe electrical environment	Damage to components, cascading effects in system	2	Med - High	2

6. Discussion & Conclusion

The use of FMEA in this work allowed for the identification of potential failure modes for a Battery Energy Storage System, the assessment of the risks associated with these failure modes, the ranking of issues in terms of importance, and the identification of some of the detection methods within the system to address the most serious concerns. Combining it with tools like ROADS enables using the probabilities that a component could fail via a specific mode and cause.

Despite the BESS utilizing second-life batteries, the components identified as having the highest risks are those responsible for its functionality and maintaining an optimal environment, such as the Battery Management System (BMS) and the cooling system. These components have more than one high-risk failure mode identified. Having detection methods for the identified failures helps reduce the risk. Based on the results of this FMEA, attention should be paid to safety-critical components including the chillers, BMS controller and various sensors. Detection and mitigation methods that can prevent or reduce the probability of these failures occurring should be investigated.

FMEA and FMECA have significant drawbacks, which affected the performance of this work as well. Assembling the necessary information for the FMEA process is particularly time-consuming, as it requires a strong technical basis for the analysis. Detailed knowledge of the system is essential, including previous failures and their probabilities of reoccurrence. Additionally, the process demands familiarity with system diagrams, descriptions, failure databases, and hazard checklists—ideally assigned to a team of three to five experts who thoroughly understand the system's operation. Furthermore, significant amounts of information are needed to quantify an FMECA. At a minimum, the system's design must be well-understood, along with the various physical and phenomenological dependencies between components to accurately propagate failure modes. Finally, capturing accurate failure rates requires either significant system and component failure data or reliance on generic component databases (e.g., ROADS) at the loss of model fidelity.

7. Future work

The work completed so far marks the initial phase of conducting the intended risk assessment. While several critical components for the system's functionality have already been identified, additional items still need to be added to gain a more accurate understanding of the risks of component failure.

The next step in this work will incorporate Bayesian Networks (BNs) to produce diagnostic and prognostic reliability models of the system. Combining FMEA with BNs provides a way to mitigate potential risks specific to system failures and supports more effective risk management strategies (Ruiz-Tagle et al. 2022). Additionally, BNs can track how failures propagate throughout the system, offering a deeper understanding of potential cascading effects.

Another avenue to explore is verifying whether the use of Model-Based Systems Engineering (MBSE) could benefit the study. Some MBSE software tools can perform reliability analysis on system models. Using such tools might simplify the process of tracking failures and determining whether they could trigger other failures within the system.

References

Aerospace Recommended Practice. 2020. “Recommended Failure Modes and Effects Analysis (FMEA) Practices for Non-Automobile Applications.”

Birkl, Christoph R., Matthew R. Roberts, Euan McTurk, Peter G. Bruce, and David A. Howey. 2017. “Degradation Diagnostics for Lithium Ion Cells.” *Journal of Power Sources* 341 (February):373–86. https://doi.org/10.1016/j.jpowsour.2016.12.011.

“Concepts - Cameo Safety and Reliability Analyzer 19.0 LTR - No Magic Documentation.” n.d. Accessed December 2, 2024. https://docs.nomagic.com/display/CSRA190/Concepts.

Conzen, Jens, Sunil Lakshmipathy, Anil Kapahi, Stefan Kraft, and Matthew DiDomizio. 2023. “Lithium Ion Battery Energy Storage Systems (BESS) Hazards.” *Journal of Loss Prevention in the Process Industries* 81 (February):104932. https://doi.org/10.1016/j.jlp.2022.104932.

Coron, E., S. Geniès, M. Cugnet, and P. X. Thivel. 2020. “Impact of Lithium-Ion Cell Condition on Its Second Life Viability.” *Journal of The Electrochemical Society* 167 (11): 110556. https://doi.org/10.1149/1945-7111/aba703.

Faessler, Bernhard. 2021. “Stationary, Second Use Battery Energy Storage Systems and Their Applications: A Research Review.” *Energies* 14 (8): 2335. https://doi.org/10.3390/en14082335.

Fan, Ersha, Li Li, Zhenpo Wang, Jiao Lin, Yongxin Huang, Ying Yao, Renjie Chen, and Feng Wu. 2020. “Sustainable Recycling Technology for Li-Ion Batteries and Beyond: Challenges and Future Prospects.” *Chemical Reviews* 120 (14): 7020–63. https://doi.org/10.1021/acs.chemrev.9b00535.

G. Lacey, G. Putrus, and A. Salim. 2013. “The Use of Second Life Electric Vehicle Batteries for Grid

Support." In *Eurocon 2013*, 1255–61. https://doi.org/10.1109/EUROCON.2013.6625141.

Gabryelczyk, Agnieszka, Svetlozar Ivanov, Andreas Bund, and Grzegorz Lota. 2021. "Corrosion of Aluminium Current Collector in Lithium-Ion Batteries: A Review." *Journal of Energy Storage* 43 (November):103226. https://doi.org/10.1016/j.est.2021.103226.

Goldman Sachs. 2024. "AI Is Poised to Drive 160% Increase in Data Center Power Demand." May 14, 2024. https://www.goldmansachs.com/insights/articles/AI-poised-to-drive-160-increase-in-power-demand.

Hendricks, Christopher, Nick Williard, Sony Mathew, and Michael Pecht. 2015. "A Failure Modes, Mechanisms, and Effects Analysis (FMMEA) of Lithium-Ion Batteries." *Journal of Power Sources* 297 (November):113–20. https://doi.org/10.1016/j.jpowsour.2015.07.100.

Huang, Bin, Zhefei Pan, Xiangyu Su, and Liang An. 2018. "Recycling of Lithium-Ion Batteries: Recent Advances and Perspectives." *Journal of Power Sources* 399 (September):274–86. https://doi.org/10.1016/j.jpowsour.2018.07.116.

Liu, Qianqian, Chunyu Du, Bin Shen, Pengjian Zuo, Xinqun Cheng, Yulin Ma, Geping Yin, and Yunzhi Gao. 2016. "Understanding Undesirable Anode Lithium Plating Issues in Lithium-Ion Batteries." *RSC Advances* 6 (91): 88683–700. https://doi.org/10.1039/C6RA19482F.

Martinez-Laserna, Egoitz, Elixabet Sarasketa-Zabala, Igor Villarreal Sarria, Daniel-Ioan Stroe, Maciej Swierczynski, Alexander Warnecke, Jean-Marc Timmermans, Shovon Goutam, Noshin Omar, and Pedro Rodriguez. 2018. "Technical Viability of Battery Second Life: A Study From the Ageing Perspective." *IEEE* Transactions *on Industry Applications* 54 (3): 2703–13. https://doi.org/10.1109/TIA.2018.2801262.

N. Guru, S. Patnaik, M. R. Nayak, and A. K. Barisal. 2024. "Renewable Energy Sources and Battery Storage Integrated Microgrid Energy Management for Customer Benefit with Reduced Emission." In *2024 IEEE* International *Conference on Smart Power Control and Renewable Energy (ICSPCRE)*, 1–6. https://doi.org/10.1109/ICSPCRE62303.2024.10674826.

O'Kane, Simon EJ, Weilong Ai, Ganesh Madabattula, Diego Alonso-Alvarez, Robert Timms, Valentin Sulzer, Jacqueline Sophie Edge, Billy Wu, Gregory J Offer, and Monica Marinescu. 2022. "Lithium-Ion Battery Degradation: How to Model It." *Physical Chemistry Chemical Physics* 24 (13): 7909–22.

Prasad, Shiv, Krishna Kumar Yadav, Sandeep Kumar, Priti Pandita, Javed Khan Bhutto, Maha A. Alreshidi, Balasubramani Ravindran, Zaher Mundher Yaseen, Sameh M. Osman, and Marina M. S. Cabral-Pinto. 2024. "Review on Biofuel Production: Sustainable Development Scenario, Environment, and Climate Change Perspectives − A Sustainable Approach." *Journal of Environmental Chemical Engineering* 12 (2): 111996. https://doi.org/10.1016/j.jece.2024.111996.

Quanterion Solutions Incorporated. 2024. "Reliability Online Automated Databook (ROADS)." 2024. https://roads.quanterion.com/search.

Ruiz-Tagle, Andres, Austin D. Lewis, Colin A. Schell, Ernest Lever, and Katrina M. Groth. 2022. "BaNTERA: A Bayesian Network for Third-Party Excavation Risk Assessment." *Reliability Engineering & System Safety* 223 (July):108507. https://doi.org/10.1016/j.ress.2022.108507.

Shahjalal, Mohammad, Probir Kumar Roy, Tamanna Shams, Ashley Fly, Jahedul Islam Chowdhury, Md. Rishad Ahmed, and Kailong Liu. 2022. "A Review on Second-Life of Li-Ion Batteries: Prospects, Challenges, and Issues." *Energy* 241 (February):122881. https://doi.org/10.1016/j.energy.2021.122881.

Sharma, Kapil, and Shobhit Srivastava. 2018. "Failure Mode and Effect Analysis (FMEA) Implementation: A Literature Review," April.

Steckel, Tobiah, Alissa Kendall, and Hanjiro Ambrose. 2021. "Applying Levelized Cost of Storage Methodology to Utility-Scale Second-Life Lithium-Ion Battery Energy Storage Systems." *Applied Energy* 300 (October):117309. https://doi.org/10.1016/j.apenergy.2021.117309.

U.S. Energy Information Administration. 2024. "Electricity Data Browser - Net Generation for All Sectors." 2024. https://www.eia.gov/electricity/data/browser/.

X. Hu, X. Deng, F. Wang, Z. Deng, X. Lin, R. Teodorescu, and M. G. Pecht. 2022. "A Review of Second-Life Lithium-Ion Batteries for Stationary Energy Storage Applications." *Proceedings of the IEEE* 110 (6): 735–53. https://doi.org/10.1109/JPROC.2022.3175614.