DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING

EEL 4920 – SENIOR DESIGN I

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Battery Diagnostic & Prognostic Tool Application

TEAM 10

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SENIOR DESIGN I PROPOSAL

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ABSTRACT

This project focuses on developing a Battery Diagnostic and Prognostic Tool to improve lithium-ion battery health monitoring and predictive maintenance. Current battery management systems (BMS) effectively monitor the State-of-Charge (SOC) but struggle to provide accurate, long-term insights into the State-of-Health (SOH). Our tool integrates machine learning (ML) techniques and hardware-in-the-loop (HIL) simulations to address this gap and deliver precise lifespan predictions, failure forecasts, and real-time diagnostics.

The tool operates as a full-stack hybrid application, supporting cloud-based and offline functionality to ensure reliability in diverse environments. Key activities involved interviews with potential users, surveys to gather feature requirements, and iterative design development, prioritizing compatibility with legacy systems and energy efficiency. Using simulation data and real-world testing, we evaluated the system’s ability to predict battery performance accurately.

The results indicate that our tool enhances battery monitoring capabilities, reduces waste by extending battery life, and promotes safer energy storage practices. This project addresses societal needs for sustainable energy solutions and contributes to our professional development by advancing our understanding of ML integration, real-time diagnostics, and system design.

I. Executive Summary

Battery Diagnostic and Prognostic Tool Application	
Team Number: 10	Team Name: Li-Logic
Team Mentor: Dr. Arif Sarwat	Team Leader: Franko Sanabria
Team Member: Roberto Valdes	Team Member: Joshua Natal
Team Member: Sebastian Munoz	Team Member: Jacob Stafford

A. *Summarized Problem Statement*

The degradation and failure of Li-ion batteries in battery management systems pose significant challenges regarding reliability, safety, and maintenance. Current diagnostic and prognostic tools are often limited by a lack of user-friendly interfaces, insufficient integration with cloud systems, and inadequate use of advanced technologies like machine learning (ML) and artificial intelligence (AI). These limitations hinder the ability to predict failures, diagnose issues, and recommend actionable solutions efficiently.

B. *Objectives and Constraints*

1) *Safety:*

The system must comply with safety standards for Li-ion batteries, including thermal and electrical safety.

2) *Accuracy:*

Diagnostics and prognostics must provide reliable and precise metrics such as State of Charge (SoC) and State of Health (SoH).

3) *Accessibility:*

The platform must feature an intuitive interface for users of varying technical expertise.

4) *Cloud Integration:*

Seamless integration with cloud services for real-time monitoring and data storage.

5) *Standards Compliance:*

The system must adhere to industry standards for batteries, cloud systems, and AI/ML applications.

6) *Cost-Effectiveness:*

The solution should be affordable and scalable for widespread adoption.

C. *Project Description*

The proposed system is a comprehensive Battery Diagnostic and Prognostic Tool application designed to improve the management of Li-ion batteries in BESS. It includes the following components:

- **Diagnostic Sensors**: Monitor critical parameters such as voltage, temperature, and capacity.
- **Battery Management System (BMS)**: Analyzes sensor data to calculate SoC, SoH, and other key metrics.
- **Cloud System**: Enables remote access, real-time updates, and data visualization.
- **User Interface**: A platform with a login/signup system and a dashboard that displays connected devices. Users can select devices to access detailed metrics such as SoC, SoH, and inverter status.
- **Machine Learning**: Implements predictive analytics to forecast battery performance and recommend maintenance actions.

D. *Sections*

The most important sections that are comprised within this document are:

1) *Background:*

This section outlines the current state of Li-ion battery technology, industry challenges, and the gaps in existing diagnostic tools. It highlights the increasing demand for reliable energy storage systems in industries such as renewable energy, transportation, and telecommunications.

*2) **Needs and Feasibility Analysis***:
This section assesses the necessity and practicality of the proposed tool. It includes evaluating technical requirements, market demand, and the feasibility of integrating diagnostic sensors, cloud computing, and AI into a cohesive system.

*3) **End Product Description**:*
The final tool will feature a login/sign-up platform and a user-friendly dashboard for managing devices, advanced diagnostics (providing SoC, SoH, and trend analysis over time), real-time monitoring with alerts for potential failures, and cloud-based data access for remote diagnostics and maintenance.

*4) **Budget**:*
This section provides a detailed breakdown of costs, including hardware components (e.g., sensors, microcontrollers), cloud services, software development, and testing. The goal is to maintain affordability while ensuring high-quality performance.

*5) **Results Evaluation**:*
Success metrics will include:

- Diagnostic accuracy for SoC and SoH measurements.
- User satisfaction with the platform's interface and functionality.
- Reduction in unexpected battery failures and maintenance costs.
- Scalability and adaptability to various use cases, such as home energy systems or industrial BMS.

Given the growing reliance on energy storage systems in various industries, this project addresses a critical market need for reliable, user-friendly, and cost-effective battery diagnostic tools. By integrating advanced technologies and adhering to best practices, the solution aims to set a benchmark for the next generation of battery management systems. Through this senior design project, we will gain valuable experience in embedded systems, cloud integration, and AI/ML applications, preparing us for future challenges in the field of energy systems.

II. Problem Statement

A significant need for better battery health monitoring and predictive maintenance in energy storage systems is addressed by developing an advanced Li-Ion battery prognostic and diagnostic tool. While State-of-Charge (SOC) can be effectively monitored using current battery management techniques, it can be challenging to determine the State-of-Health (SOH) of individual batteries, modules, or complete systems over an extended period. This restriction results in unrealistic performance, shorter battery life, and the potential for system malfunctions. This project intends to improve battery monitoring by combining Machine Learning (ML) and Artificial Intelligence (AI) approaches to provide precise lifespan estimates, failure forecasts, and real-time diagnostics. The goals and limitations of this project are described in detail in the following sections, providing a thorough rundown of the design and development objectives.

*A. **Project Objectives***

The primary objectives of this project are:

- To create a battery diagnostics full-stack hybrid remote/cloud application that functions in both local and cloud settings.
- To guarantee that the system can be offline after deployment in remote locations with erratic network connectivity.
- To incorporate machine learning (ML) and reinforcement learning (RL) monitoring tools and controls into the diagnostic procedure.
- Determine the best ML/RL algorithms for cloud services and real-time edge processing to guarantee peak performance.
- To create a hardware-in-the-loop (HIL) simulation to verify the diagnostic tools' real-time control performance.
- To improve the diagnostic tool, deploy the finished system on an actual battery pack and compare the outcomes of the lifespan study with simulation data.

*B. **Constraints***

When creating the Li-Ion battery prognostic and diagnostic tool, a few critical limitations must be taken into consideration:

- When creating the Li-Ion battery prognostic and diagnostic tool, a few critical limitations must be taken into consideration:
- Real-Time Data Processing: In unpredictable network connectivity, it is essential to guarantee low-latency communication between local systems and the cloud.
- Integration with Legacy Systems: To support legacy technologies, the tool may need to be specifically developed to be compatible with current battery management systems (BMS) and hardware.
- Hardware Restrictions: ML/RL models must be tailored for resource-constrained situations since edge components, like embedded battery controllers, have limited processing power and storage.
- Data security and privacy: It's crucial to safeguard private battery performance data when transmitted over the cloud, which calls for strong encryption and adherence to laws like the General Data Protection Regulation (GDPR).
- Cloud Service Costs: Cost control requires effective use of cloud resources when processing and storing massive amounts of diagnostic data across multiple devices.

- Offline Functionality: To ensure system operability without a continuous cloud connection, the tool must perform necessary diagnostic activities locally while network connectivity is unavailable.
- Energy Efficiency: The tool must use as little energy as possible while providing good diagnostic accuracy because running ML/RL models locally can increase power consumption.

III. ASSUMPTIONS AND LIMITATIONS

*A. **Assumptions***

We make some crucial assumptions when creating our full-stack, hybrid remote/cloud application for the Li-Ion Battery Prognostic and Diagnostic Tool:

- Target User Proficiency: We assume that our target users, which include engineers and battery operators, are conversant with monitoring metrics such as State-of-Charge (SOC) and State-of-Health (SOH) and possess a fundamental grasp of battery management systems (BMS).
- Hardware and Software Compatibility: We anticipate that there won't be any significant problems with hardware or software compatibility when local devices (such as embedded controllers or battery management systems) integrate with cloud services.
- Development Tool Availability: We assume that the libraries, APIs, and development tools required for integrating machine learning (ML) and reinforcement learning (RL) are easily accessible and compatible with edge and cloud processing.
- Network Availability: Local processing capabilities will manage diagnostics when offline, and network connectivity—albeit somewhat erratic in remote settings—will be adequate to permit sporadic cloud connection.
- Data Accuracy and Reliability: We anticipate that battery system data will be accurate and dependable, allowing for the appropriate training of machine learning models for predictive maintenance and diagnostics.
- Compatibility with Battery Management System (BMS): We anticipate that the diagnostic tool will work with current BMS technology and be able to be implemented without requiring significant hardware changes.
- Cybersecurity procedures: We anticipate that sensitive data will be safeguarded during transmission between local devices and the cloud by regular encryption techniques and cybersecurity procedures.

*B. **Limitations***

The creation of this battery prognostic and diagnostic tool is limited in several ways despite our best efforts:

- Real-Time Data Processing: Establishing a low-latency connection between local systems and the cloud might be challenging, particularly in settings with unstable networks.
- Hardware Restrictions: The complexity of machine learning (ML) models that may be executed locally is restricted by edge devices' processing power and memory.
- Cloud Costs: Using cloud platforms to store and analyze massive amounts of data can be costly; proper resource management is needed to remain cost-effective.
- System Compatibility: Because of antiquated hardware configurations, integrating with historical Battery Management Systems (BMS) may present technical difficulties.
- Security and Privacy: There are hazards associated with sending battery data to the cloud. Thus, strong encryption and adherence to privacy laws are required.
- Energy Consumption: ML models may use more power when running on battery-operated devices, which could shorten battery life.
- Development Time: Limited because the academic calendar restricts testing and iterative improvements.

In summary, even if the project recognizes difficulties with hardware constraints, system integration, and real-time data processing, these limitations guide our design strategy. We aim to provide a workable, dependable, and reasonably priced solution for Li-Ion battery health monitoring by carefully addressing these issues.

IV. NEEDS FEASIBILITY ANALYSIS

A Needs Feasibility Analysis greatly aids in developing a Battery Diagnostic and Prognostic Tool, specifically in providing a comprehensive set of objectives and other relevant metrics to realize the product's feasibility and potential to be marketed to a global audience. By understanding the client's requirements and the applications it can provide to users, we can determine the trajectory of our design process.

The challenges in estimating parameters such as the State of Charge (SOC) and State of Health (SOH) in modern Li-Ion batteries are crucial to the growing need for accurate battery management solutions. Introducing machine learning (ML) techniques for this tool, such as a feedforward neural network (FNN) or recurrent neural network (RNN), adds another layer of complexity that must be evaluated to make this project feasible. [1] It will need to be created so that the system is scalable to meet the needs of diverse users, who may vary from individual hobbyists to electric vehicle manufacturers.

Thus, our team will conduct interviews, disseminate surveys, and research the market to create a streamlined and realistic product. These efforts will enable us to identify the most critical features and ensure the application is user-friendly and commercially viable.

*A. **Needs Analysis***

This section will detail the need analysis our team has delineated. The need analysis will aid in our understanding of the intended users for our product and reinforce the goal of creating an easy-to-use and efficient application that will provide valuable insights. We will cover the interview conducted with the client, survey data gathered, and an organized set of objectives and constraints for our project.

1) Client

Our first action in the need analysis process was interviewing the client to determine the requirements for the application. The following table provides some attributes specific to the client’s needs.

TABLE 1: PRELIMINARY REQUIREMENTS GATHERED FROM THE CLIENT

Source	Attribute	Type
Client	The system must operate offline (local) and online (cloud-based) for data collection and processing.	Versatility
Client	The system should be deployable in varying environments (local computers, Raspberry Pi, or other means)	Versatility
Client	Machine Learning techniques must be implemented for battery health monitoring and data processing.	Accuracy & Reliability
Client	The application should involve real-time control for battery performance validation.	Accuracy & Reliability
Client	The application must be functional in both simulated and real-world environments.	Versatility
Client	The application should have a predictive maintenance feature.	Accuracy & Reliability
Client	The tool must provide secure cloud storage for remote access and monitoring.	Data Handling
Client	The application should have a user-friendly interface.	Ease of Use
Client	Documentation should be provided so users can reference it for the tool's operation.	Ease of Use

2) *Survey*

After speaking with the client and gathering some preliminary requirements, we created a survey for potential users to determine which features would have a lasting impact on the product's success. Once again, these were organized into attributes, which are organized by category, as shown in Table 2.

TABLE 2: SURVEY RESULTS FROM POTENTIAL USERS. THE SURVEY WAS DISSEMINATED TO PEOPLE WITHIN THE UNIVERSITY COMMUNITY, SPECIFICALLY ELECTRICAL AND COMPUTER ENGINEERING STUDENTS.

Source	Attribute	Type
Survey	The application should be available to deploy on a PC, Raspberry Pi, or mobile application *(in that order of preference)*	Versatility
Survey	The application must work online (cloud-connected) and offline (local) modes.	Versatility
Survey	The application should have a user-friendly interface.	Ease of Use
Survey	The application should have real-time monitoring.	Accuracy & Reliability
Survey	The application should have a predictive maintenance feature.	Accuracy & Reliability
Survey	The data gathered by the application must be accurate and in real-time.	Accuracy & Reliability
Survey	The application should be easily integrated with other environments (such as the cloud)	Versatility
Survey	The application should offer advanced features.	Versatility
Survey	The application should have a reasonable cost.	Ease of Use
Survey	The application should be able to predict the lifespan of the battery.	Accuracy & Reliability

3) *Proposed Plan*

To ensure that the results gathered from multiple sources adequately aid in forming objectives and constraints, we also conducted an internal survey within the team to get a consensus for what features will take priority.

TABLE 3: INTERNAL SURVEY RESULTS FROM THE DESIGN TEAM

Source	Attribute	Type
Survey	The application should be deployable on a PC, Raspberry Pi, or mobile, with a preference for a PC.	Versatility
Survey	The application must work online (cloud-connected) and offline (local) modes.	Versatility
Survey	The application should have a user-friendly interface.	Ease of Use
Survey	The application should have real-time monitoring for battery metrics (voltage, temperature).	Accuracy & Reliability
Survey	The application must include a predictive maintenance feature.	Accuracy & Reliability
Survey	The data gathered by the application must be accurate, with occasional syncing being sufficient.	Accuracy & Reliability
Survey	The application should be easily integrated with other environments (such as the cloud)	Versatility
Survey	The application should have a reasonable cost.	Ease of Use
Survey	The application should have advanced features, which are second to core functionality.	Accuracy & Reliability

4) Project attributes

After gathering information from the client, potential users, and the team's opinions via an internal survey, we determined which features to prioritize in our project. The following table demonstrates the list of combined attributes that will be feasible within our desired timeline.

TABLE 4: FINAL DESIGN ATTRIBUTES SELECTED BASED ON INTERVIEWS, SURVEYS, AND TEAM BRAINSTORMING

Source	Attribute	Type
Combined	The application should be deployed on a PC as the primary platform.	Versatility
Combined	The application must work online (cloud-connected) and offline (local) modes.	Versatility
Combined	The application should have a user-friendly interface.	Ease of Use
Combined	The application should have real-time monitoring for battery metrics (voltage, temperature).	Accuracy & Reliability
Combined	The application must include a predictive maintenance feature.	Accuracy & Reliability
Combined	The data gathered by the application must be accurate and synced during critical events or hourly.	Accuracy & Reliability
Combined	The application should be easily integrated with other environments (such as the cloud)	Versatility
Combined	The application should have a reasonable cost.	Ease of Use
Combined	The application should have advanced features, but core functionality will be prioritized.	Accuracy & Reliability

The analysis conducted through interviews, survey results, and design team brainstorming has cemented a clear set of goals for our application. Features like real-time monitoring, cloud connectivity, and predictive maintenance will be at the core of the application’s capabilities. Creating a PC-based application is pertinent to our timeline, as we intend to have a preliminary application ready to use in the months leading up to its final iterations.

5) Problem Statement

Creating an advanced Battery Diagnostic and Prognostic Tool Application for lithium-ion batteries is essential for promoting battery health monitoring and providing intuitive features such as predictive maintenance for users and organizations. Current methods for assessing battery health parameters, such as the State of Charge (SOC) or State of Health (SOH), have laid the groundwork for better battery management practices. However, the need to analyze large datasets from Battery Management Systems to make predictions about the performance of batteries is critical for innovation, the adoption of sustainable habits by the industry, and other pertinent practices for users. This will help reduce current suboptimal battery performance, extend the life of lithium-ion batteries, and prevent potential system failures that could pose a safety risk. Introducing Machine Learning (ML) and Reinforcement Learning (RL) techniques will significantly enhance battery monitoring by informing users of lifetime projections, failure predictions, and real-time diagnostics.

6) Objectives

The primary objectives of this project include:

- Develop a full-stack, hybrid remote and cloud-based application for battery diagnostics, ensuring synergy between local and cloud environments.
- Make sure the system can support offline use after it is deployed, especially in cases where there may be limited network connectivity, with regular data syncing in place during critical events or hourly intervals.

- Integrate machine learning (ML) and reinforcement learning (RL) techniques into the diagnostic process to improve real-time monitoring capabilities, support predictive maintenance habits, and improve overall battery health assessment.
- Identify and implement suitable ML/RL algorithms to optimize performance and accuracy in real-time edge processing and cloud services.
- Create a hardware-in-the-loop (HIL) simulation for validation of real-time control performance of the diagnostic tools before it is deployed.
- Ensure accuracy and real-time monitoring for critical battery metrics like voltage and temperature while maintaining ease of integration with cloud platforms.
- Provide a user-friendly interface that allows easy navigation and data interpretability, thus providing accessibility for technical and non-technical users.
- Deploy the final system to a genuine battery pack and compare lifecycle analysis results with simulation data to improve upon predictive maintenance features.

7) Constraints

Several constraints need to be considered when developing this application, which include:

- Low latency communication between local systems and the cloud is crucial, especially when network connectivity is intermittent.
- This application must be compatible with existing battery management systems (BMS) and hardware, which can involve customization to support legacy technologies.
- The ML/RL models being implemented must be optimized for resource-constrained environments, as is when working with edge devices such as embedded battery controllers.
- Users' data regarding sensitive battery performance must be protected during transmission to the cloud, utilizing encryption techniques and compliance with privacy regulations.
- Cost-effectively managing cloud resources is essential, even when processing and storing large volumes of diagnostic data.
- The tool must function in offline environments, performing essential diagnostic tasks when network connectivity is unavailable.
- While the application operates, it must be energy efficient, even if ML/RL models utilized locally are known for higher power consumption.

*B. **Need Specification***

Given the initial survey results, our interview with the client, and our analysis of the operating environment, we were able to gather a set of specifications. These specifications are outlined in the following table to satisfy the desired features from potential users and the client. Moreover, these specifications will provide a framework for our team to create a minimum viable product from which we can receive feedback for future improvements.

TABLE 5: NEED SPECIFICATION FOR BATTERY DIAGNOSTIC AND PROGNOSTIC TOOL APPLICATION

Objective	Specification	Justification
1a	The system must operate within a temperature range of -20°C to 60°C.	Lithium-ion batteries are vulnerable to variations in temperature, which can affect their performance & lifespan. Thus, it must work in extreme conditions.
1b	System enclosure should meet IP65 or higher standards for dust and moisture protection. This is if the product is deployed on a microcontroller like a Raspberry Pi.	To prevent the failure of electronic components, these standards help the system operate in extreme environments.
2a, 2b	The system must support real-time monitoring of battery metrics (voltage, current, temperature, etc.).	Real-time monitoring is vital for maintaining battery performance & providing accurate diagnostics.
3a	The system should be deployable locally (PC, Raspberry Pi) and on cloud platforms.	We provide users with online and offline capabilities that align with their versatility objectives.
4a, 4b	The system must include machine learning (ML) & reinforcement learning (RL) algorithms for predictive maintenance and real-time diagnostics.	It helps improve accuracy in battery health predictions and failures.
5a, 5b	The system must support data transmission with low latency (<1 second is optimal) and high bandwidth.	Low latency improves response for real-time monitoring, while high bandwidth helps accommodate large datasets.
6a	The system should offer secure cloud storage with encryption for remote access & monitoring via Microsoft Azure.	Ensures data security and privacy, especially for sensitive battery performance data.
7a	The system should provide a user-friendly interface with easy data interpretability and streamlined navigation.	A straightforward interface can help make the app accessible to technical and non-technical users.
8a	The system must be compatible with existing Battery Management Systems (BMS) and support legacy hardware.	Compatibility with BMS systems can help ease its introduction into various industries.

Considering these specifications, we can design a preliminary diagnostics application that meets the client's and users' needs while providing our team with a transparent and manageable framework. This will aid in creating a minimum viable product, which will be tested in the field and then iteratively improved to ensure the final product is accurate and reliable while protecting users' interests.

*C. **Feasibility Analysis***

When developing a product, it is essential to conduct a feasibility analysis to determine how practical and viable our idea, which is to create a machine learning-based tool for assessing battery health, is to realize in a real-world setting. This feasibility analysis considers various factors that can contribute to this realization, and they are categorized into technical, resource, scheduling, cultural, legal, and marketing feasibility. The analysis entails asking a few questions to assess how they can be solved, and then they are quantified into a score ranging from 1.0 to 5.0 because of the answers. Once quantified, the scores are modified to visualize one factor's overall importance over another via combined and weighted scores. Finally, these weighted scores are used to deliver a final score, which is emblematic of the project's overall feasibility.

1) *Technical Feasibility*

Technical feasibility assesses whether the technology our team intends to use is available and accessible for the product to be realized. It is also determined to call into question whether implementing these technologies is challenging to attain. Table 6 shows these technological issues, resulting in an average score of 4.4.

TABLE 6: TECHNICAL FEASIBILITY WEIGHT SCALE

Attributes	Score	Why?	Solution
Can an Artificial Neural Network accurately predict battery health and life expectancy?	4.0	While ANNs can handle large datasets, battery data can vary significantly depending on usage, making it challenging to generalize predictions accurately.	Use a large, diverse dataset to train the ANN and optimize the hyperparameters for improved accuracy.
Can a Flask API efficiently handle data collection and serve as a user interface?	4.5	Flask is a lightweight web framework that can be used to build APIs and UIs to an extent, but its simplicity could limit performance with a high user load.	Consider using Flask with caching and load balancing to handle larger data requests.
Can Microsoft Azure support our computational requirements for model training and inference?	5.0	Azure offers scalable computing resources and ML tools ideal for our project.	Utilize Azure's Machine Learning services and scale up resources as needed.
Are compatible tools available for integrating machine learning, API, and cloud infrastructure?	4.5	Tools for integration are available, but careful configuration is necessary for seamless connectivity.	Use Azure SDKs for Python and Flask for efficient API and cloud interaction.
Are new methods and techniques required for battery data processing?	4.0	Battery diagnostic and prognostic modeling is complex and may require innovative preprocessing techniques.	Experiment with data augmentation and normalization techniques to improve model reliability.
Total	22.0		
Average	4.4		

2) *Resource Feasibility*

Resource feasibility is another factor in our feasibility analysis, which inquiries about the availability of resources for our product. If the resources we intend to use are scarce or difficult to obtain, our project's viability could be affected. Table 7 depicts these possible resource-related dilemmas, resulting in an average score of 4.2.

TABLE 7: SOURCE FEASIBILITY WEIGHT SCALE

Attributes	Score	Why?	Solution
Do we have sufficient skills in machine learning model development?	3.5	Our team consists of four EE majors and one CE major, and while some of us have taken introductory courses in machine learning, only one has research experience in ML-based device modeling.	Leverage the research of our team member in ML modeling and seek guidance from faculty and graduate students knowledgeable in battery diagnostics.
Do we have sufficient skills to implement a Flask API and user interface?	4.0	Although some team members have experience in web development, this is our first project using Flask specifically.	Utilize Flask documentation and online tutorials, and collaborate closely with our CE major, who may have more programming experience.
Do we have the necessary cloud computing knowledge to utilize Microsoft Azure?	3.5	Only two of our team members have worked with cloud platforms, and Azure is new to most of the team.	Have the experienced members lead Azure integration and complete structured tutorials for the rest of the team to ensure familiarity.
Do we have access to suitable equipment for testing and development?	5.0	We have access to computers, software, and the necessary tools for testing through our university resources.	No additional solution is needed.
Do we have a sufficient number of team members to handle this workload?	5.0	Our team, which comprises five members, allows us to distribute workload effectively across various project tasks.	No solution is required.
Total	21.0		
Average	4.2		

3) Economic Feasibility

For a project to be economically feasible, it must be evaluated from a fiscal perspective to determine where specific challenges may lie, from production costs and the like. Table 8 shows this in more detail, resulting in an average score of 4.6.

TABLE 8: ECONOMIC FEASIBILITY WEIGHT SCALE

Attributes	Score	Why?	Solution
Are software and cloud resources affordable?	4.5	Microsoft Azure offers affordable student plans, and Flask is open-source, which reduces costs. However, if scaling is necessary, Azure services could become costly.	Start with Azure's student plan and scale up resources as needed.
What is the risk of software or model training errors?	4.0	Training machine learning models require multiple iterations, which can increase cloud computing costs, but careful planning can control this.	Thoroughly plan model training states and troubleshoot locally as much as possible before deploying on Azure.
Are equipment and hardware costs affordable?	5.0	We have access to lab equipment at no additional cost, which minimizes our need for external purchases.	No additional solution is required.
What is the cost risk of acquiring data for model training?	5.0	We can gather simulated data from the lab and access and create real-time data using a BMS. However, more specific data regarding edge cases could incur expenses if needed.	Use the lab to generate datasets and explore free or low-cost data sources if additional data is required.
Total	18.5		
Average	4.6		

4) Schedule Feasibility

Scheduling feasibility entails our team evaluating the timeline we have set out to complete the project. We will need to question whether we can effectively meet the deadlines we set and manage our time efficiently. Table 9 highlights this evaluation, resulting in an average score of 4.3.

TABLE 9: SCHEDULING FEASIBILITY WEIGHT SCALE

Attributes	Score	Why?	Solution
What is the likelihood of meeting the planned milestones?	4.5	Our team has created a structured timeline, balancing each project component. However, we may need help with model training or Flask API integration, which could cause delays.	Follow a structured schedule with milestone check-ins and contingency plans. Dedicate time each week to track and adjust as needed.
What is the likelihood of meeting the Preliminary Design Review (PDR) requirements?	4.0	Early-state design issues could come up, especially with integrating machine learning components. We will need time to refine these before PDR.	Focus on the core functionality of the product and avoid feature creep. Keep initial goals achievable and align PDR requirements with fundamental project objectives.
What is the likelihood of meeting the Critical Design Review (CDR) requirements?	4.5	With access to a lab and testing equipment, we can rigorously test and troubleshoot as we approach CDR. A well-defined testing phase is planned.	Schedule frequent testing in the lab to identify issues early, ensuring reliability by CDR. Document all test outcomes for rapid resolution.
Total	13.0		
Average	4.3		

5) Cultural Feasibility

Cultural feasibility is necessary to determine how well our battery diagnostic and prognostic tool meshes with cultural norms and preferences. If there are any challenges regarding how our product will be culturally accepted, it is evaluated here. Table 10 depicts these cultural-related issues, resulting in an average score of 4.4.

TABLE 10: CULTURAL FEASIBILITY WEIGHT SCALE

Attributes	Score	Why?	Solution
Will there be a positive impact on the domestic audience?	4.5	Battery health monitoring is becoming increasingly crucial in energy-conscious communities. Our tool supports this trend by offering a convenient solution to extend battery life.	Emphasize the tool's role in promoting sustainable battery use and long-term cost savings, aligning with domestic environmental awareness.
Will there be a positive impact on the international audience?	4.0	Globally, interest in battery diagnostics is high, particularly in regions with growing renewable energy adoption. Cost and accessibility could be limitations for some audiences.	Highlight the tool's adaptability and potential for integration with various battery types and applications to appeal internationally.
Are there any potential objections related to data privacy?	4.5	Data privacy concerns may arise, especially with personal or proprietary battery data being used in the cloud.	Ensure data handling complies with local regulations and provide clear communication on privacy protections in place.
Could there be any ethical or environmental objections?	4.5	Battery disposal and recycling are significant concerns, and our tool may be seen as encouraging responsible usage by reducing waste.	Market the tool as a solution that supports sustainable battery management, potentially extending battery life and reducing waste.
Total	17.5		
Average	4.4		

6) *Legal Feasibility*

Legal feasibility involves evaluating whether our diagnostic and prognostic tool follows relevant laws, regulations, and intellectual property rights. We must consider any potential challenges related to legal compliance and any risks in infringing on any existing tools out there. Table 11 illustrates these legal issues, resulting in an average score of 4.5.

TABLE 11: LEGAL FEASIBILITY WEIGHT SCORE

Attributes	Score	Why?	Solution
Are there any legal roadblocks or regulations affecting the project?	4.5	The team reviewed battery diagnostics and prognostics patents to avoid infringement risks. Thorough patent research minimizes potential conflicts.	Ensure compliance with relevant intellectual property by avoiding patented methods, such as impedance spectroscopy. (detailed in our Intellectual Property section)
Are there any organizational or policy conflicts?	4.5	The BMS market has established standards for safe operation and EMI (electromagnetic interference) control. Non-compliance with these standards could be problematic.	Adhere to industry standards and conduct thorough testing for compliance with FCC and IEEE requirements.
Total	9		
Average	4.5		

7) Marketing Feasibility

Marketing feasibility entails determining whether the target market will well receive our product and how it can be promoted and accepted. We must consider potential market acceptance and competition risks to ensure our product is successful. Table 12 shows these marketing-related concerns, resulting in an average score of 4.2.

TABLE 12: MARKETING FEASIBILITY WEIGHT SCORE

Attributes	Score	Why?	Solution
Will the general public accept the product?	4.5	Battery health monitoring tools are gaining interest across consumer and industrial markets, especially with the rise of renewable energy and EVs.	Emphasize the tool's ability to extend battery life and support sustainable practices, appealing to eco-conscious customers.
How will it compare with similar products?	4.0	Competing tools exist in the market, but some offer a machine learning-based approach that affordably combines diagnostics and predictive features.	Position our product as a cost-effective, advanced solution for accurate battery monitoring.
Will it be accessible to users in multiple industries?	4.0	The tool's versatility can appeal to electric vehicle manufacturers, renewable energy companies, and general consumers, but specific use cases vary.	Market the tool as adaptable to multiple battery applications, ensuring it meets industry-specific needs where possible.
Total	12.5		
Average	4.2		

8) *Feasibility Ranking*

To rank our overall feasibility, we compared each type of feasibility with one another to create weights. This is visualized in Table 13, where each feasibility type in every row is compared with another feasibility in columns. The resulting values are used to rank each attribute's importance, which is quantified as follows:

- 1 = Equal importance
- 3 = Moderately more important
- 5 = Strongly more important
- 7 = Extremely more important

Table 13 also shows the geometric mean, calculated from the weights of every attribute and normalized to equal one. The geometric mean is found using Equation (1).

$$G.Mean = (A_1 * A_2 * A_3 \ldots * A_n)^{1/n} \qquad (1)$$

Where A is the importance value given to each attribute, and n is the total number of attributes. Then, the normalized weight of each attribute is shown in Table 13 using Equation (2).

$$Weight = \frac{G.Mean}{Total} \qquad (2)$$

TABLE 13: FEASIBILITY WEIGHTS

	Technical	***Resource***	***Economic***	***Schedule***	***Cultural***	***Legal***	***Marketing***	***G. Mean***	***Weight***
Technical	1	5	5	3	3	7	5	3.60	0.38
Resource	0.2	1	3	3	3	5	3	1.87	0.20
Economic	0.2	0.33	1	3	3	5	3	1.37	0.15
Schedule	0.33	0.33	0.33	1	3	5	3	1.08	0.11
Cultural	0.33	0.33	0.33	0.33	1	3	3	0.73	0.08
Legal	0.14	0.2	0.2	0.2	0.33	1	0.5	0.29	0.03
Marketing	0.2	0.33	0.33	0.33	0.33	2	1	0.47	0.05
							Total	9.41	

9) *Overall Project Feasibility*

After calculating the feasibility weights shown in Table 13, the weighted score and average can be calculated and tabulated. Table 14 depicts the overall success probability of our project, which is calculated using Equation (3).

$$Weighted\ Score = Weight * Score \qquad (3)$$

After the weighted scores are calculated, they are added and placed in Equation (4) to be divided by the sum of weighted scores, leading to the weighted average.

$$Weighted\ Average = \frac{\sum Weighted\ Score}{\sum Weight} \qquad (4)$$

TABLE 14: FEASIBILITY WEIGHTED SCORE

	Weight	Score	W. Score
Technical	0.38	4.4	1.68
Resource	0.20	4.2	0.84
Economic	0.15	4.6	0.67
Schedule	0.11	4.3	0.49
Cultural	0.08	4.4	0.34
Legal	0.03	4.5	0.14
Marketing	0.05	4.2	0.21
Total	1	30.6	4.37
Weighted Average			4.37

The weighted average of 4.37 out of 5 indicates that our project is highly likely to succeed. We must focus on technical implementation and manage resources effectively to secure this outcome.

*D. **Marketability***

Better battery health monitoring is more important than ever due to the rising popularity of renewable energy storage systems and electric vehicles. The inability of current energy storage technologies to accurately estimate battery conditions frequently results in subpar performance and possible problems. More sophisticated technologies on the market use artificial intelligence (AI) and machine learning (ML) to anticipate battery failures and extend battery life. Our initiative seeks to meet this demand and significantly improve battery management systems by providing lifespan estimates, real-time diagnostics, and early failure detection.

1) Project 1: SuperBase V

a) Project Summary

The SuperBase V energy storage system, developed by **Zendure Inc.** in Palo Alto, CA, offers an advanced solution for residential and mobile energy applications. Launched on Kickstarter in 2022, the project quickly gained traction by raising over $5 million. SuperBase V integrates a smart Battery Management System (BMS) with AI-driven diagnostics, enabling it to monitor battery health, predict failures, and optimize energy usage. Its success drew attention from homeowners, outdoor enthusiasts, and renewable energy advocates due to its innovative approach to sustainable energy management [9].

b) Funding Strategy

SuperBase V provided multiple reward tiers, including early access to the product, branded gear, and extended warranty options. This tiered reward system incentivized different contribution levels and engagement from the backers.

c) Technology Overview

The system uses a combination of lithium-ion batteries, BMS, and AI algorithms to optimize battery life and energy consumption. Its key features include seamless connectivity with other smart home systems and real-time energy usage tracking.

d) System Description

SuperBase V’s block diagram Fig. 1 shows how energy flows from solar panels into the storage system, where AI optimizes its distribution. The system uses sensors to track battery health and ensure maximum efficiency.

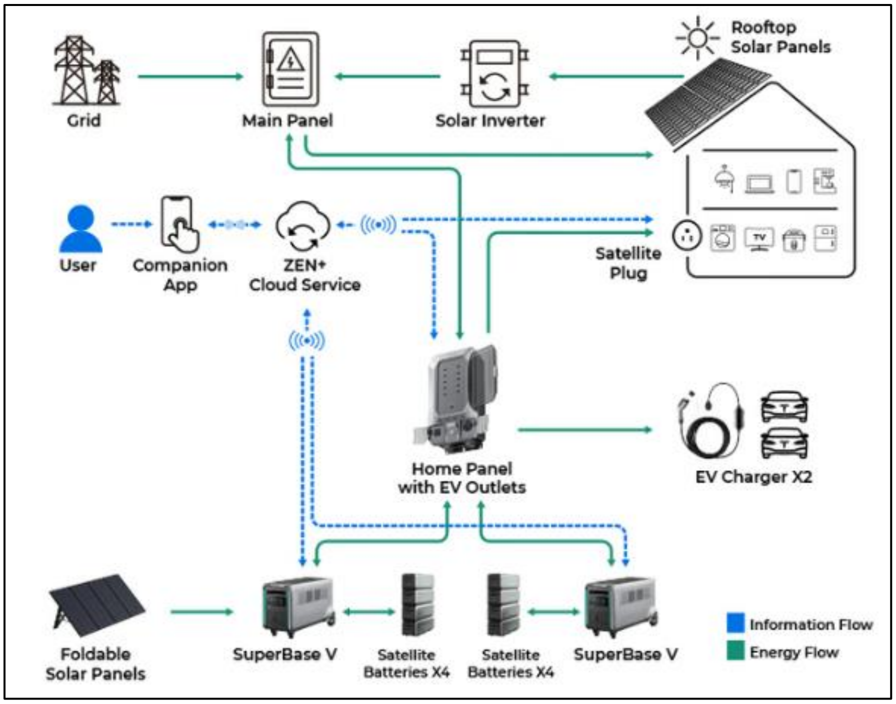


Fig. 1: Block diagram for SUBERBASE V [9]

2) *Project 2: EcoFlow DELTA Pro [10]*

a) Project Summary

EcoFlow DELTA Pro is another home energy storage solution designed for high-capacity use. This portable home battery system, introduced by EcoFlow, is perfect for off-grid living and residential backup because of its expandable capacity of up to 25 kWh. The project highlights its versatility by combining various power sources, such as solar and grid energy.

b) Funding Strategy

The reward structure for the EcoFlow DELTA Pro Kickstarter campaign begins at $500 for an accessory, allowing backers to support the project without committing to the full system. For those seeking the complete package, higher-tier rewards offer the full DELTA Pro unit, with prices reaching up to $3,000. Early project supporters are incentivized with discounts on the entire energy storage system and additional accessories, creating a compelling reason to invest early and at various commitment levels.

c) Technology Overview

The EcoFlow DELTA Pro has a lithium-ion battery that offers numerous features, such as solar charging, compatibility with electric vehicle (EV) charging, and fast recharging capabilities. Because of its adjustable battery capacity, the system can be used for a wide range of energy requirements. It has a smart energy management system that enables customers to remotely monitor and regulate their energy consumption using a mobile app and several charging choices, including solar, grid, and electric vehicles. Because of these properties, it is a flexible and practical energy solution for domestic and mobile applications.

d) System Description

The system is designed to connect to both the grid and renewable energy sources. It features a smart home panel that automatically allows users to switch between different power sources in case of outages.

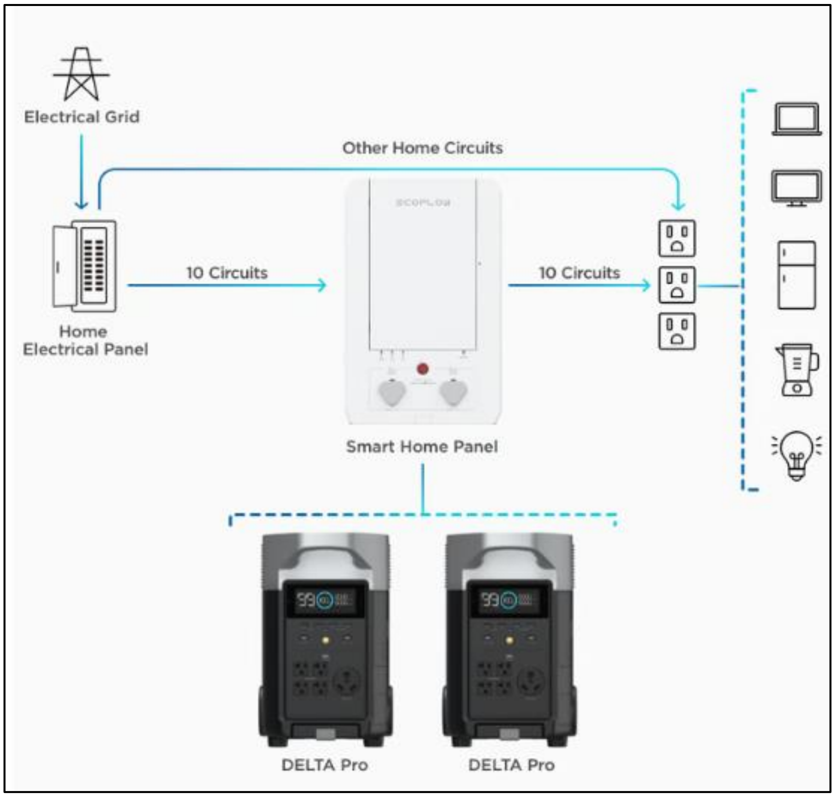


Fig. 2: Block Diagram for ECOFlow DELTA Pro [10]

If we were to make a fundraising effort inspired by these successful Kickstarter initiatives, we would offer early access to our diagnostic tool, exclusive upgrades, and tailored services for more prominent contributors if we were to launch a fundraising effort. We might interact with funders on several levels via a tiered reward structure, raising the possibility of broad adoption. Sites like Kickstarter or Shark Tank perfectly demonstrate the project's inventiveness and ability to address practical energy storage problems.

V. RISK ANALYSIS

Within every engineering project, there lies uncertainty over some of its aspects, and because of it, there may or may not be risks involved in completing each task. Therefore, we as engineers must develop a plan to mitigate these potential risks so they can be prevented or dealt with accordingly. By adequately assessing these probable issues, the project can move forward so that each risk is classified and categorized concerning severity and urgency and addressed well in advance. As such, the risk analysis does just that in this section.

Our team has reviewed risks based on each category identified in the feasibility analysis. These risks were then evaluated regarding the probability of their realization and the severity they would entail if they were to impact the project. Subsequently, a plan is created to minimize risks within the project's timeline.

The following categories of risks, along with their specific risks, are detailed using the fault tree fishbone diagram in Fig. 3:

- Technical Feasibility

  T1. Making sure that sensors and diagnostics accurately record battery health metrics

  T2. Creating predictive algorithms that can reliably forecast battery performance

  T3. Ensuring the tool works across multiple battery configurations

  T4. Integrating hardware and software (Raspberry Pi to Microsoft Azure, for example) without compromising functionality

  T5. Need for regular model updates to maintain prediction accuracy, which will require more cloud resources and testing

  T6. Managing the complexity of ML models on resource-limited edge devices

  T7. Potential latency issues when syncing real-time data between local and cloud components
- Resource Feasibility

  R1. Limited availability of diverse battery types for testing

  R2. Making sure we have sufficient resources to process and store diagnostic data

  R3. Limited access to datasets that cover all possible usage scenarios
- Economic Feasibility

  E1. Risk of surpassing the budget for sensors and components

  E2. Incurring additional costs for maintaining and replacing equipment

  E3. Higher than expected cloud computing costs when scaling up
- Schedule Feasibility

  S1. Balancing project work with academic commitments

  S2. Delays in testing due to limited access to the lab or necessary equipment

  S3. Potential delays in receiving specialized hardware, like the Raspberry Pi

  S4. Extra time is needed for iterative testing of our ML model
- Cultural Feasibility

  C1. Skepticism from the community towards an ML predictive algorithm for battery health
- Legal Feasibility

  L1. Making sure our collection of data is compliant with privacy regulations

  L2. Adhering to industry safety and testing standards for battery diagnostics

  L3. Compliance with data processing regulations for cloud storage

- Market Feasibility
  M1. Difficulty standing out in a competitive battery diagnostics market
  M2. Users may find the tool too complex or costly to operate compared to alternatives
  M3. Challenges in meeting diagnostic and data standards seen in the industry

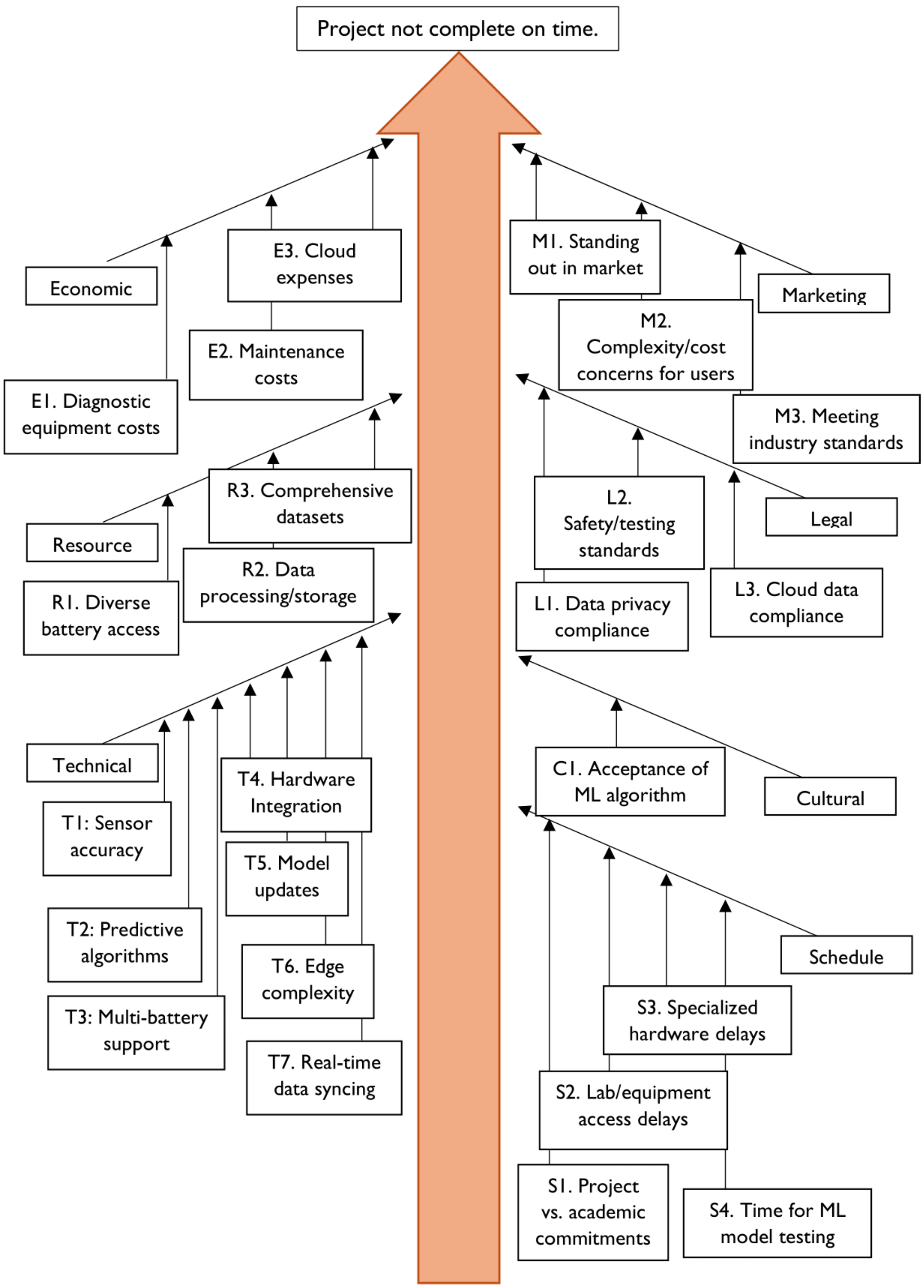


Fig. 3: Fault tree analysis fishbone diagram

A fishbone diagram helps determine any inherent risks associated with a project and conducts a root cause analysis. Thus, our team utilized this analysis to identify the risks involved in our project and develop a plan for mitigation and prevention.

After executing the fault tree analysis, the risks were organized into categories using an exposure matrix. An exposure matrix categorizes each risk into ranks based on class and the likelihood of the occurrence. Class I risks are typically the least severe and don't require immediate attention or an active mitigation plan. Class II risks are more severe and fall upon what is known as the risk threshold, and therefore, they must be monitored with careful detail. Class III risks exceed the threshold and require the utmost attention and proactive mitigation. Class IV risks are the most severe and must be handled immediately. A likelihood of occurring accompanies each risk and falls under one of three ranks: unlikely, potential, or very likely. Combining the probability of the occurrence with the risk class provides the rankings in Table 15, which can range from Low Risk to Catastrophic Risk.

TABLE 15: RISK EXPOSURE MATRIX

Risk Severity	**Likelihood of Occurrence**			***Legend***
	Very Likely	***Possible***	***Unlikely***	
Class IV Immediate attention				Catastrophic Risk
Class III Proactive management		M1	E3, S3, M2	Severe Risk
Class II Active monitoring		T1, T5, R1, R2, R3, E1, L1, L3	T4, T6, E2, S1, C1, L2	Moderate Risk
Class I Below threshold	S2	T2, T3	T7	Low Risk

After the exposure matrix was populated and the risks were categorized, developing a strategy to minimize each risk became pertinent. Although machine-learning-based battery diagnostics is relatively new and could be an asset to users, several technical feasibility risks must be carefully considered while harnessing control over other factors. These factors can involve increased spending on cloud computing if our product scales to larger applications than initially anticipated, as one might find when tailoring it to electric vehicle manufacturers. Table 16 draws from this set of categorized risks and details an action step to assess each proactively.

TABLE 16: ACTIONS TO MINIMIZE RISK

Cell	Risks	Actions
I - Unlikely	T7	Create a buffer for data transfer to minimize latency; test data syncing capability regularly and adjust as needed to prevent significant delays.
I – Possible	T2	Periodically conduct validation of predictive algorithms under varied battery conditions; adjust parameters used based on performance to increase reliability.
I – Possible	T3	Prioritize the application's core functionality before expanding product capability for multiple configurations.
II – Unlikely	T4	Run pre-integration tests of the hardware-to-cloud communication before fully assembling the product; check for any compatibility issues that might arise that could affect performance.
II – Unlikely	T6	Make changes to ML parameters to reduce complexity when considering edge devices; prioritize essential features for smooth operation.
II – Unlikely	E2, S1	Track expenses closely and create a plan to handle unexpected costs by having backup options for equipment and alternate times to meet in the lab so disruptions are minimized.
II - Unlikely	C1	Create a help guide and transparent documentation on ML use to mitigate skepticism from the community.
II – Unlikely	L2	Ensure our product development is aligned with industry standards; prioritize key safety elements during prototyping without fully certifying unless necessary.
I – Very Likely	S2	Reserve lab time and create a shared schedule; document tests to account for potential limitations in lab access.
II – Possible	T1	Ensure sensors are calibrated and validated before starting the project and disseminate findings amongst team members.
II – Possible	T5, R1, R2, R3	Identify external datasets for ML model training if needed; create a plan to share data and allocate resources amongst team members.
II – Possible	E1	Keep track of expenses for core components and adjust the budget in the event of unexpected cost increases.
II - Possible	L1, L3	Review data handling procedures to ensure compliance with privacy standards and document storage practices for security purposes.
III – Unlikely	S3	Order any specialized hardware early and coordinate with the sponsor to avoid delays in critical components.
III – Unlikely	M2	Make user interface easy to use and gather feedback via testing to improve tool accessibility.
III – Unlikely	E3	Set alerts for cloud computing usage and review cost reports regularly to stay within budget.
III - Possible	M1	Emphasize that our tool can predict accuracy and engage with users for input on desired features.

As evidenced by the above table, this list of action items will help our team proactively manage any risks that may arise, especially regarding marketability, technical feasibility, and economic factors, to name a few. Our team must have cohesive communication and a disciplined approach to meeting our deadlines to mitigate these risks with plenty of time to spare.

Our team must clearly understand the risks involved when undergoing a long-term project. As such, we can implement mitigation tactics to have a well-rounded product that prioritizes accuracy and reliability.

VI. Operating Environment

The operating environment is a fundamental aspect that is crucial when defining a project's overall design and specifications. For the Li-ion battery prognostic system in particular, this section will provide details catered towards explaining how our product can be affected by external conditions. These conditions include but are not limited to temperature, humidity, and electrical noise. As for the cloud environment, some conditions that need to be considered are scalability, processing power, and latency. These elements substantially impact the precision and dependability of performance measurements and forecasts, especially considering the characteristics of batteries and real-time monitoring systems. In this section, we will go over some of the more impactful environmental factors and how we plan to account for them.

*A. **Temperature***

Temperature is one of the critical environmental components to take into account. Because Li-ion batteries are more susceptible to temperature changes, their performance and lifespan may suffer. The prognostic system must be built to work in a wide range of temperatures (-20°C to 60°C), particularly in industrial or automotive applications where batteries might be used in harsh or outdoor conditions. Monitoring elements like voltage sensors, current sensors, and battery management system (BMS) modules must continue to function accurately within specified temperature ranges. Temperature-compensation algorithms will be implemented into the system’s software to offset the effects of high or low temperatures, changing capacity predictions accordingly.

*B. **Humidity and Moisture***

Another environmental issue is humidity since too much moisture can cause electronic components to corrode and malfunction, resulting in sensors or communication interface failure. Because of this, the system requires an enclosure that affords protection from dust and water and has a high IP (Ingress Protection) rating—at least IP65 [8]. Sealing techniques and protective coatings on circuit board components will be used in locations like mines, factories, or coastal regions where moisture levels are unpredictable to prevent condensation buildup or prolonged exposure to excessive humidity.

*C. **Electrical noise and interference***

Controlling the system's electrical noise sensitivity is also essential, particularly in locations where electromagnetic interference (EMI) is expected, like factories with lots of electronic equipment or industrial sites with extensive machinery. EMI can distort sensor readings and obstruct data flow between components. To minimize interference and maintain clear data transmission, the battery's voltage, current, and temperature sensors will use shielded cables, ground planes on circuit boards, and noise-filtering algorithms.

*D. **Latency and bandwidth***

The system will transfer real-time battery data via a cloud connection; therefore, network latency and available bandwidth are essential. Environments with low latency provide prompt monitoring and replies, particularly for real-time battery status updates. More excellent bandwidth guarantees that big datasets, such as charging cycles, voltage records, and other telemetry, are handled effectively.

E. ***Availability and scalability***

High availability should be a feature of the cloud platform to guarantee uninterrupted system functioning around the clock. Furthermore, the cloud infrastructure should be scalable when the system grows to accommodate more users, devices, or data streams. Horizontal (adding more servers to the system) and vertical scaling (increasing resources to existing servers) are needed.

F. ***Processing power***

Processing power will be needed for real-time battery health monitoring, trend analysis, and predictive algorithms. To run complex algorithms quickly, cloud providers provide a variety of methods for dynamically scaling computational resources based on system demand.

To sum up, by considering the factors mentioned above, the design of the battery prognostic system will be able to function reliably in various settings. The system can be modified to satisfy the requirements of different operating conditions by considering these factors. By doing this, the system offers trustworthy forecasts on battery health and life in practical settings. By integrating these difficulties into the design, the general performance of the battery, its efficiency, safety, and the accuracy of the models and data can be enhanced.

VII. INTENDED USER(S) AND INTENDED USE(S)

A. Intended User(s)

The primary users of our battery prognostic and diagnostic tool would start with car manufacturers and range down to the lowest levels of car mechanics. You can categorize all of these into:

1) Electric vehicle manufacturers:
    a) **Effect on Specs:** The amount of data collected from the battery of an electric vehicle will be considerably more than the average non-electric vehicle. Using that as a baseline means the machine learning algorithm will have to be able to sort through more extensive sets of data as a precaution.
    b) **Customization:** Users of electric vehicles rely more on the battery than any other vehicle out there, so they will get the most benefits and be more willing to use the software to predict battery loss.
2) Gas/Diesel vehicle manufacturers:
    a) **Effect on specs:** Manufacturers of gas vehicles have smaller batteries, which are significantly cheaper. Extending battery life will have a negligible impact. Still, it will affect the individual customer more than with an electric vehicle, meaning being able to sort through a smaller amount of data, machine learning still needs to sort through it and provide decent results.
    b) **Cost:** Putting this software into every available vehicle on the road makes the price jump significantly, so making the software run on cheaper hardware to reduce the overall price and make it more accessible to the general public will help.
3) General car mechanics:
    a) **Effect on specs:** The user interface must be able to be used by an average noncollege-educated individual. Easy to use and easy to understand the information. Getting rid of the non-essential data and only showing things that would help the general mechanic diagnose and understand the battery's health will be the main priority at this level.
    b) **Reliability:** The general mechanic can measure the individual cells, but there is no way to check the overall health of each cell. Changing this could make the battery check a routine thing that happens when you get an oil change or check your tires. Doing this means that the data given must be reliable and not just guess that the battery will die soon when it's not.

B. Intended Use(s)

The primary uses of the battery prognostic and diagnostic tool would range from routine battery checks to helping to design better batteries for the future.

1) Routine battery checks:
    a) **Effect on specs:** Having the battery checked four or five times a year means that the data needs to be able to be sorted so it's stored and sorted by when it is being checked and as a total. Keeping this in mind will make two different data sets stored within one data set.
    b) **Integration with the average devices:** Compatibility with every different type of device is crucial when installed on all other types of cars and all different types of batteries. Making this available on phones of various kinds will allow us to make it easily accessible to all.

2) Developing new batteries:
   a) **Effect on specs:** For use in laboratories, the data needs to be grabbed, sorted, and accessible in real time so that you can see real-time results. Increasing the amount of data you take in at one time will also increase the accuracy of the data.
   b) **Precision and ease of access:** High-quality equipment needs to be reliable, and when dealing with electronics in general, being a little bit off can change everything. Making this as precise as possible will help when you need to adjust and can help figure out flaws in the battery.

After going through all the users and uses of all the different groups, we can reliably make a device that anyone can use on almost any platform anywhere in the world. Starting and ending with the information provided will help create a new system and change how we view batteries.

VIII. BACKGROUND

Over time, battery health monitoring and predictive maintenance have changed dramatically, and industries have increasingly relied on advanced diagnostic tools due to their accuracy and dependability. This chapter examines three prominent battery health monitoring tools and proof of concepts. We can pinpoint crucial aspects for enhancement and novelty in our battery health monitoring initiative by analyzing their advantages, disadvantages, and distinctive qualities. Our product's design and functional requirements are defined, and the current market offerings are comprehended thanks to this comparative analysis.

Before creating our sophisticated battery prognostic and diagnostic tool, we must look at other people's ideas, projects, and research papers. There is competition in the market for battery health monitoring, with many research papers offering a range of features to give comprehensive diagnostic and prognostic tools. Our goal is to create a tool that, at a better performance than current solutions, can provide precise lifetime projections, failure predictions, and real-time diagnostics by utilizing contemporary machine learning (ML) and artificial intelligence (AI) techniques. We need a solid understanding of what has already been developed to design the tool.

Our research has identified three notable research papers with similar design ideas close to our project goals:" Machine Learning Applied to Electrified Vehicle Battery State of Charge and State of Health Estimation," " Cloud-Based Artificial Intelligence Framework for Battery Management System" and " Smart Lithium-Ion Battery Monitoring in Electric Vehicles:" Each research paper integrates sophisticated modeling and analysis techniques to deliver high-quality diagnostics and prognostics. Through analyzing these products, we aim to identify essential features and innovations that will help guide the development of our tool and ensure that it meets the needs of modern industries.

*A. **Machine Learning Applied to Electrified Vehicle Battery State of Charge and State of Health Estimation: State-of-the-Art***

1) Project Summary

Machine Learning for Estimating the State of Health and Charge of Electrified Vehicle Batteries: Current State-of-the-Art. In an article published in March 2020 in [7], Carlos Vidal, Pawel Malysz, Phillip Kollmeyer, and Ali Emadi from McMaster University offer a thorough analysis of the use of machine learning (ML) techniques for the estimation of the state of charge (SOC) and state of health (SOH) in batteries used in electrified vehicles. Given how crucial precise battery monitoring is for electric vehicles (EVs), the study examines data-driven approaches. It emphasizes the advantages of machine learning (ML) over more conventional estimation methods like Kalman filters and equivalent circuit models (ECMs). [7]

By utilizing the growing amount of battery data available, machine learning techniques such as feedforward neural networks (FNNs), recurrent neural networks (RNNs), support vector machines (SVMs), and radial basis function (RBF) networks provide enhanced accuracy and robustness in real-world applications. The study discusses the importance of fine-tuning machine learning (ML) architectures for particular use cases, like fluctuating temperatures and distinct battery chemistries, to improve battery longevity, safety, and performance in electric vehicle batteries. [7]

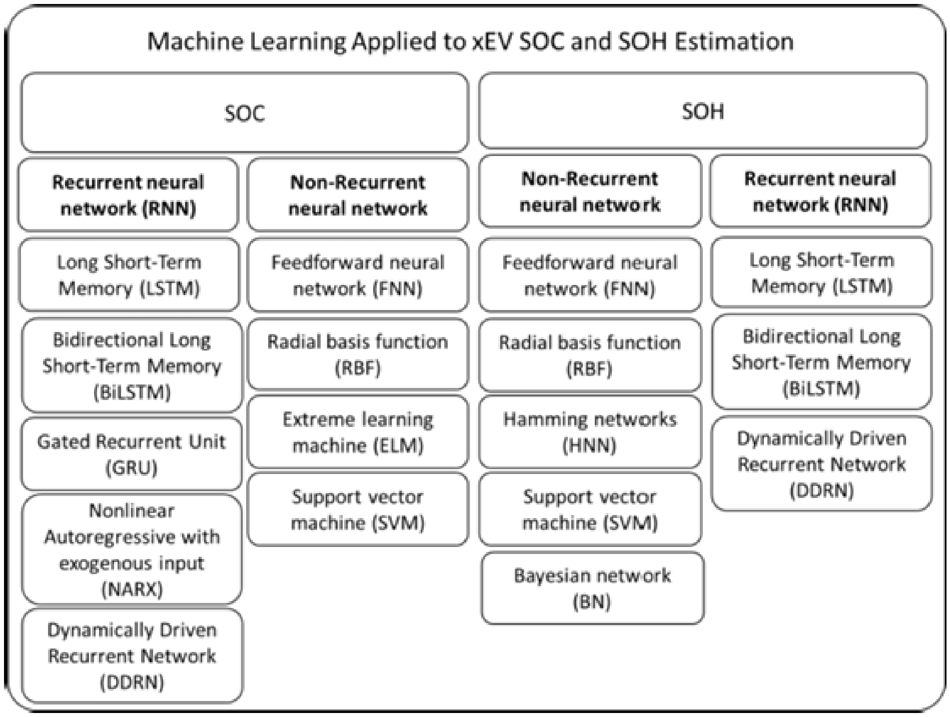


Fig. 5: Structured summary of the ML methods considered and analyzed in this paper. [7]

2) Technology Overview

With an emphasis on SOC and SOH, the paper by Vidal et al. in [7] examines the expanding role of machine learning techniques in battery state estimation. Feedforward neural networks (FNN), radial basis function (RBF) networks, support vector machines (SVM), extreme learning machines (ELM), recurrent neural networks (RNN), exceptionally long short-term memory (LSTM) models are the main machine learning techniques covered. Compared to conventional methods, these machine learning techniques analyze vast datasets of battery performance data, including variables like voltage, current, temperature, and internal resistance, to produce more precise and timely predictions.

Artificial neural networks that process data in a single direction, from input to output, are known as feedforward neural networks (FNNs). FNNs have a simple architecture. FNNs can be used with filters and other models in battery state estimation to forecast SOC from voltage and current measurements. Lithium-ion batteries have been successfully used with FNNs for SOC estimation; however, the accuracy of the results varies based on the network's complexity and the caliber of the training data.

Recurrent Neural Networks (RNNs): RNNs are perfect for tracking SOC and SOH over time because they work well with time-series data, especially LSTM models. RNNs can better simulate the dynamic behavior of batteries when storing and utilizing historical data, especially when dealing with variable operational conditions like temperature variations and distinct cycles of charging and discharging. It is mentioned that LSTM networks are beneficial for managing long-term dependencies, which are typical in battery operation.

Support Vector Machines (SVMs): SVMs are frequently utilized for SOC and SOH estimation in regression tasks. They can manage non-linear relationships between inputs and outputs by employing kernel functions to translate the input data into high-dimensional spaces. SVMs work well when complex, non-linear behaviors exist in the battery data.

Extreme Learning Machines (ELMs): Unlike traditional neural networks, ELMs have faster learning rates and require less processing power. Because of this, they are a desirable choice for real-time SOC and SOH estimation, especially in onboard vehicle systems with constrained computational resources.

3) System Description

To estimate SOC and SOH, a battery management system (BMS) integrates a variety of machine learning architectures, as described by Vidal et al. in [7]. These architectures forecast the battery's condition and make modifications to enhance performance and safety based on real-time data obtained from the battery, such as temperature, current, and terminal voltage.

The collection and transmission of data from the battery's sensors is the responsibility of the Battery Management System (BMS). Voltage, current, temperature, internal resistance, and other vital parameters are monitored, and the data is sent to the machine learning models for analysis. Based on the SOC and SOH estimates produced by the machine learning models, the BMS modifies the charging and discharging cycles to help guarantee that the battery operates within safe bounds.

The BMS uses machine learning algorithms—such as FNNs, RNNs, and SVMs—covered in [7] to process incoming battery data continuously. To forecast SOC and SOH while a vehicle is operating, these models are trained offline using historical battery data and then used in real time. For example, by considering the past time steps, the LSTM models in the BMS can predict SOC with a high degree of accuracy. SVMs are employed to estimate SOH using battery degradation and internal resistance metrics.

The BMS can make real-time adjustments to maximize battery performance because the ML models are updated in real time as new data becomes available. For instance, the system can modify charging procedures or alert the user when the battery's state of health (SOH) drops below a predetermined level, signaling the need for maintenance or the impending end of the battery's life.

To guarantee accurate SOC and SOH predictions across various battery chemistries and operational scenarios, the paper highlights the necessity of extensively testing machine learning models under real-world conditions, including variations in temperature, load, and driving cycles. [7]

4) *Block Diagram*

The block diagram shows the block diagram for machine learning applied to Electrified Vehicle Battery State of Charge and State of Health Estimation: State-of-the-Art.

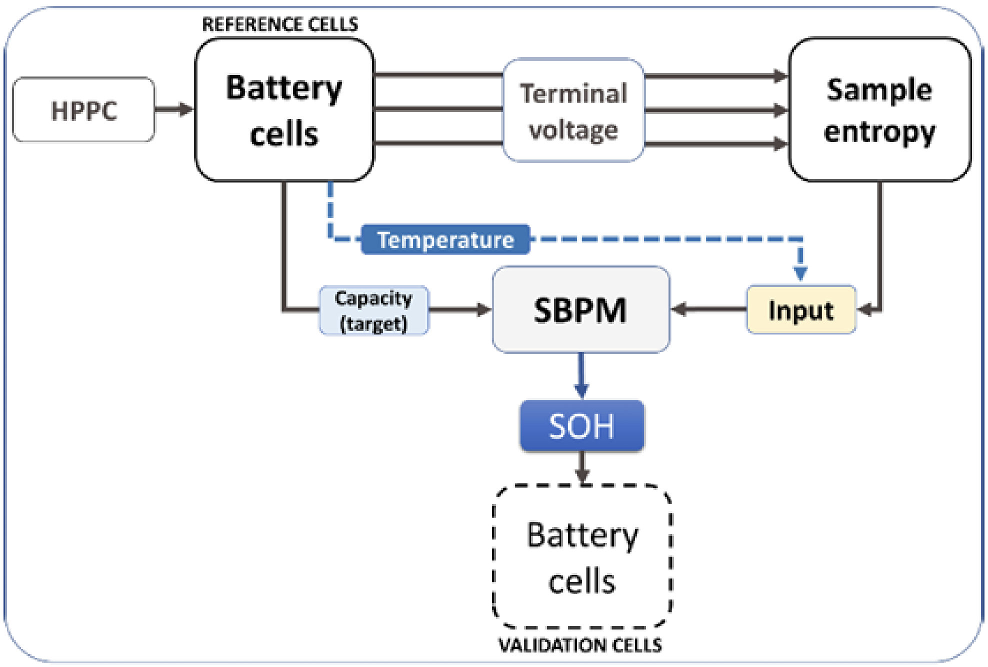


Fig. 6: Block diagram to estimate the SOHC [7]

B. *Cloud-Based Artificial Intelligence Framework for Battery Management System:*

1) *Project Summary*

A cloud-based artificial intelligence framework for battery management systems (BMS) is presented in [6] by Shi et al. from Hubei University of Arts and Science and the University of California-Davis. By combining cloud computing and artificial intelligence (AI) for improved battery management in electric vehicles (EVs) and energy storage systems, this framework overcomes the drawbacks of conventional onboard BMS. The project, which will be published in 2023, intends to address the issues brought about by the onboard BMS's constrained computational capability. These BMSs typically manage vital tasks like battery safety, state of charge (SOC), and state of health (SOH) monitoring, but they cannot adjust to changing operating conditions.

The suggested framework uses cloud computing to process and store data, enabling real-time diagnostics and sophisticated battery state prediction. The system can analyze enormous volumes of battery data by shifting intensive data processing to the cloud. This increases the precision of SOC and SOH predictions and makes predictive maintenance possible. This AI-driven solution is especially pertinent to electric vehicles, where battery performance directly impacts range, safety, and cost-effectiveness. The system gathers data from onboard sensors to maximize battery performance, processes it using machine learning algorithms in the cloud, and adjusts in real time.

By offering insights based on data-driven models, Shi et al.'s framework considerably enhances battery performance management and ensures safer and more effective battery operation under various conditions. [6]

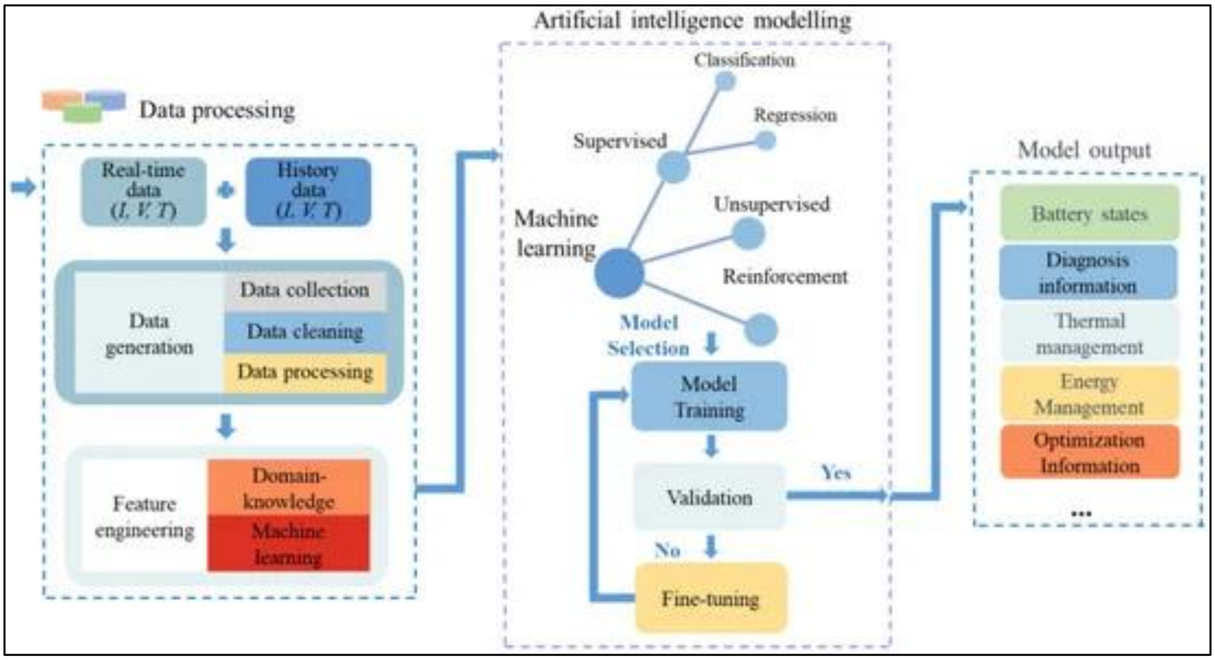


Fig. 7: AI and machine learning for modeling and predicting battery states.[6]

2) *Technology Overview*

A combination of cloud computing, machine learning, and Internet of Things (IoT) devices powers the Cloud-Based AI BMS. The AI engine is at the system's center, which analyzes battery data to provide insights into battery performance and forecast possible failures. The system is adaptive to the unique requirements of each battery it monitors because the machine-learning models are built to improve as more data is gathered continuously. [6]

Cloud computing: Cloud servers offer the processing power required to handle the enormous amounts of data produced by contemporary battery systems. The processing power of onboard BMS is restricted, and it frequently concentrates on basic tasks like SOC and SOH estimates. This framework can execute sophisticated machine learning algorithms on the cloud, enabling it to forecast battery behavior over various periods and with higher accuracy. Additionally, the cloud-based method makes real-time monitoring and remote diagnostics possible, significantly enhancing battery management—especially for large-scale deployments like fleets of electric vehicles.

Machine Learning: Machine learning models are integrated into the cloud-based framework to analyze battery data and forecast essential battery parameters. These models predict SOC and

SOH, spot degradation trends, and recommend the best charging and discharging cycles based on historical and current data. The system can reduce the risk of overcharging, thermal runaway, and early battery failure by doing this. The machine learning algorithms can generalize across different battery chemistries and use cases because they have been trained on data gathered from multiple batteries.

IoT Devices: An essential part of gathering data for this system is using IoT-enabled sensors. Incorporated into the battery pack, these sensors constantly monitor temperature, voltage, and current. The sensors send this data to the cloud using communication protocols like MQTT (Message Queuing Telemetry Transport). The system can make quick adjustments based on cloud analysis thanks to the real-time data collected from the sensors, ensuring the battery runs within its ideal performance range.[6]

3) System Description:

The Cloud-Based AI BMS system integrates multiple components, such as cloud servers, IoT sensors, and the onboard BMS, to provide a complete battery management solution. [6]

Onboard Battery Management System: Cell balancing and real-time SOC and SOH estimations are among the crucial battery monitoring duties handled by the onboard BMS. The onboard system serves as a bridge between the cloud and the battery despite having limited processing power. The cloud receives data from the BMS for additional processing and analysis.

Cloud Servers: The system's central component, cloud servers, manage all computationally demanding jobs, including storing historical data, executing machine learning algorithms, and making predictions in real-time. Following upload to the cloud, machine learning models are trained to identify anomalies, anticipate failures, and optimize battery operation processes using the data from the onboard BMS and IoT sensors. Cloud servers also enable over-the-air updates to onboard systems to guarantee that the BMS always has access to the newest algorithms and diagnostic tools.

IoT Sensors: To continuously monitor vital indicators like temperature, voltage, and current, IoT devices are embedded within the battery system. By transmitting data to the cloud for analysis, these sensors enable the system to react instantly to battery-level variations. The early identification of possible problems, such as overheating or cell imbalances, which could result in shortened battery life or safety risks, depends on this real-time data collection.

The onboard BMS and Internet of Things sensors monitor the battery's performance at the start of the system flow. The gathered data is uploaded to the cloud, where machine learning models analyze it, produce insights, and offer suggestions for maximizing battery life. The cloud platform can also remotely instruct the onboard BMS to modify configurations like charging speeds, cell balancing tactics, or thermal control procedures. This ongoing evaluation, analysis, and modification cycle guarantees that the battery will function safely and effectively for its life.[6]

4) Block Diagram:

The block diagram shows the Block diagram for the Cloud-Based Artificial Intelligence Framework for Battery Management System.

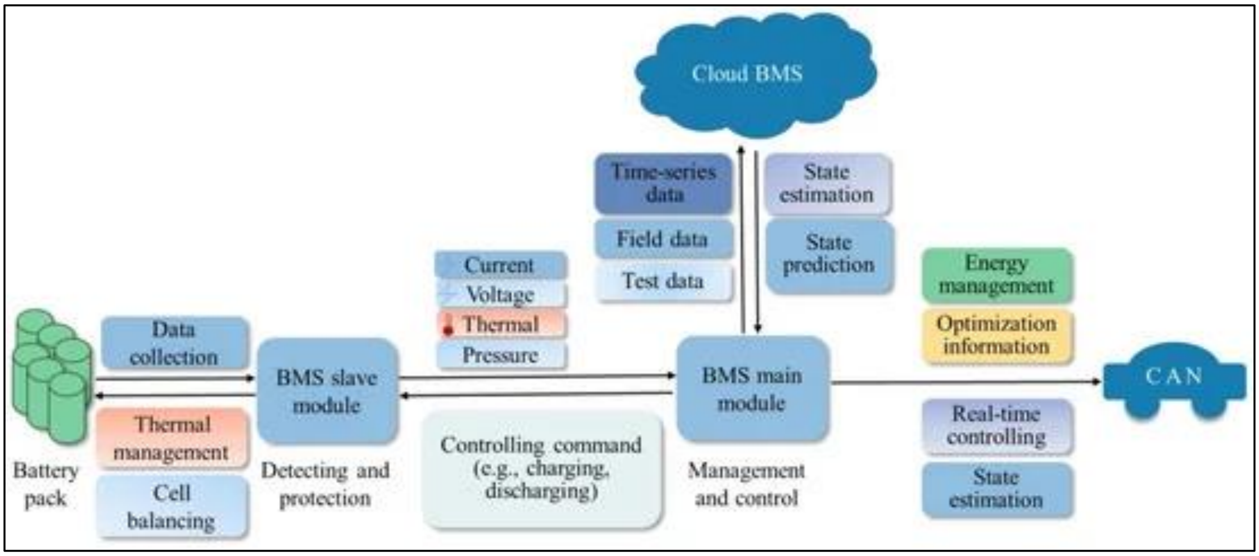


Fig. 8: Cloud-based framework for battery management in EV applications.[6]

C. ***Smart Lithium-Ion Battery Monitoring in Electric Vehicles: An AI-Empowered Digital Twin Approach***

1) Project Summary

The December 2023 publication of Smart Lithium-Ion Battery Monitoring in Electric Vehicles: An AI-Empowered Digital Twin Approach by Mitra Pooyandeh and Insoo Sohn from Dongguk University, Seoul [5] presents a revolutionary method for the monitoring of lithium-ion batteries (LIBs) in electric vehicles (EVs). To improve real-time condition monitoring and predictive analysis, the project adopts digital twin (DT) technology, a virtual duplicate of the actual battery. A seamless method of monitoring battery health and state-of-charge (SOC) is provided by the digital twin, which combines artificial intelligence (AI) with the battery management system (BMS) to eliminate the need for additional hardware. This framework leverages advanced AI techniques, including a time-series generative adversarial network (TS-GAN), to generate synthetic data that compensates for the lack of real-time data, thus improving battery performance predictions. By integrating these technologies, EVs should operate more safely and efficiently and have longer-lasting batteries.

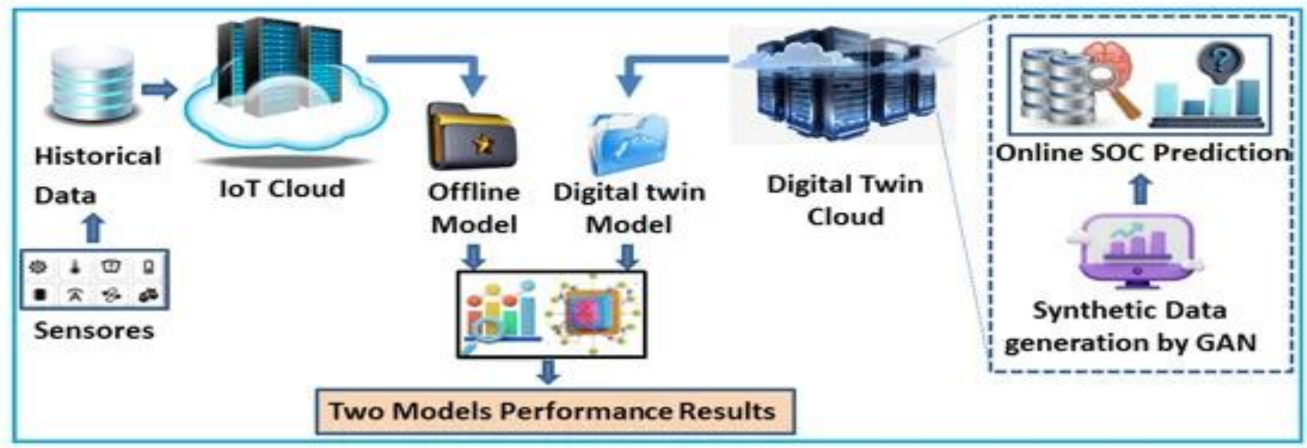


Fig. 9: Incorporated digital twin and physical system architecture for lithium-ion battery monitoring. [5]

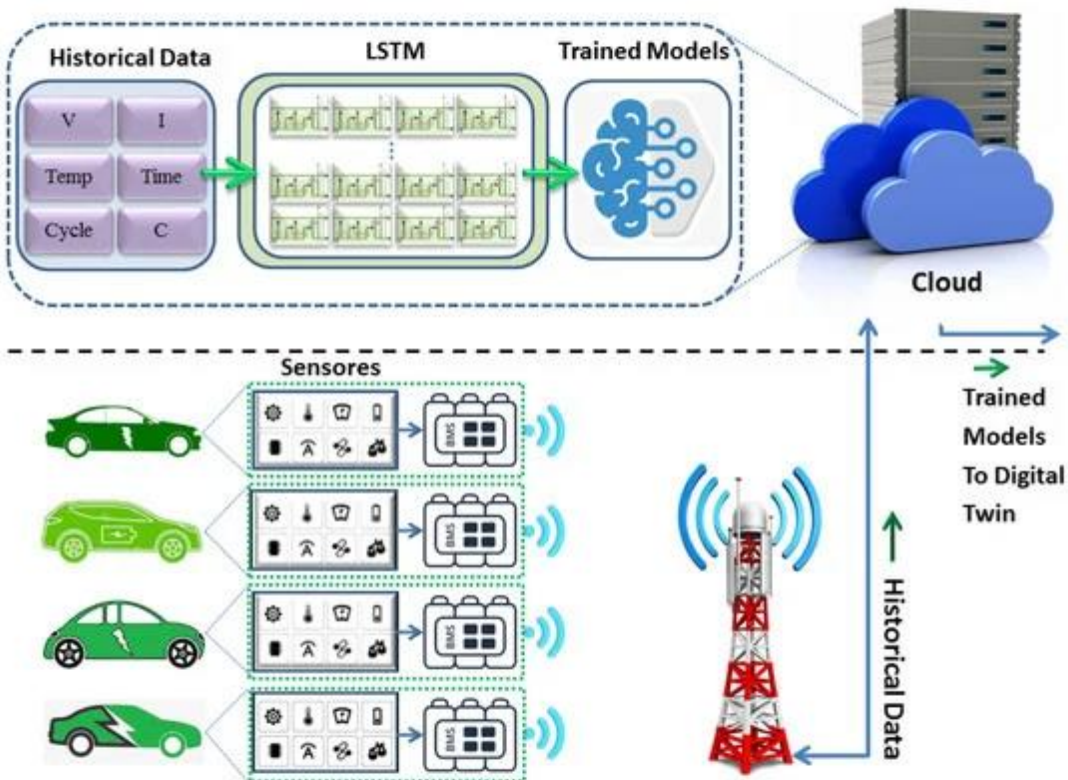


Fig. 10: Physical system architecture for lithium-ion battery monitoring. [5]

2) Technology Overview

According to Pooyandeh and Sohn [5], the digital twin and its integration with AI-driven tools like Time Series -GAN form the basis of this approach's technology. The digital twin processes relevant data such as state-of-charge (SOC), voltage, current, and temperature in real time, mimicking the behavior of the actual lithium-ion battery. The system uses long short-term memory (LSTM) neural networks to predict future battery performance, including possible problems accurately.

The digital twin is a virtualized version of the actual battery system. It is constantly being updated with real-time data from the BMS. The data is analyzed using machine learning models to predict the battery's health condition and maximize its performance. The digital twin improves operational efficiency and safety by detecting anomalies and inefficiencies.

TS-GAN: The use of Time Series addresses the problem of insufficient real-world data by offering high-quality synthetic data that simulates the behavior of actual batteries. This artificial data is added to the training dataset so that the digital twin's machine learning models can make more accurate SOC predictions. Generating this additional data enhances the system's robustness and dependability.[5]

3) System Description

According to [5], the system is constructed around two essential elements: the digital twin and the physical battery system.

The electric vehicle's onboard battery management system (BMS) is part of the physical battery system that monitors vital indicators like temperature, voltage, current, and state of charge (SOC). A cloud-based digital twin receives this real-time data continuously for additional analysis.

The digital twin replicates the physical battery by using advanced analytics to process the data the BMS collects. With this configuration, real-time SOC forecasting is possible, and battery performance can be enhanced with insights. Machine learning models—such as long short-term memory (LSTM) networks—are used to analyze the data and predict the battery's condition to ensure optimal and safe operation.

Incorporating a time-series generative adversarial network (TS-GAN), which creates synthetic data to fill in gaps in real-world data, is a noteworthy innovation highlighted in [5]. This enhancement improves the accuracy of the prediction in the system. The digital twin and physical battery constantly communicate, enhancing safety and lengthening the battery's lifespan by enabling accurate behavior forecasting and real-time monitoring.

4) Block Diagram

The block diagram shows the Digital twin framework for real-time lithium-ion battery monitoring.

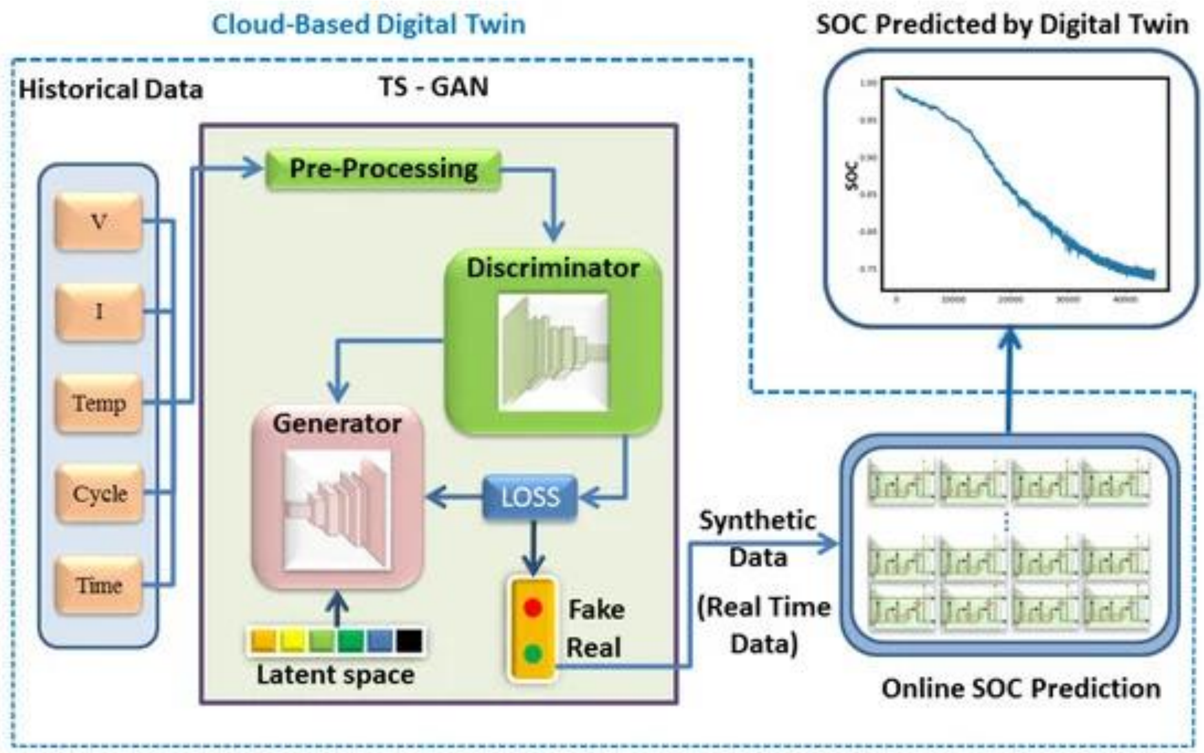


Fig. 11: Block diagram for Digital twin framework for real-time lithium-ion battery monitoring.[5]

Smart Lithium-Ion Battery Monitoring in Electric Vehicles, A Digital Twin Approach Powered by AI and Machine Learning, we've found essential breakthroughs and technologies that could improve battery management for electric vehicles in the future. These studies present cutting-edge ideas that enhance battery state monitoring, predictive maintenance, and performance optimization. Examples of these ideas include AI-driven cloud computing, digital twins, and machine learning-based estimation models. Leveraging AI, IoT, and cloud technologies enables accurate battery state prediction (SOC, SOH), real-time monitoring, and seamless data processing at scale. Our strategy will expand on these developments to provide a more intelligent and effective battery management solution.

In conclusion, analyzing these frameworks reveals the advantages and possible areas for development in the present battery management systems. The combination of cloud computing, digital twins, and machine learning models holds considerable promise for more accurate and foresighted battery state estimation. The best way to utilize real-time data and ensure that various battery types are compatible are still issues that must be resolved. Our project aims to further improve electric vehicle battery management systems, ensuring safety and performance improvements over current solutions, focusing on AI integration, real-time monitoring, and predictive analytics.

IX. Intellectual Property

The protection of intellectual property is a critical aspect of modern engineering and technological development, particularly in innovative fields such as Battery Management Systems (BMS), Artificial Intelligence (AI), and Machine Learning (ML) for energy storage applications. Proper IP due diligence is essential to prevent patent infringement, ensure the novelty of our project, and position our work as a unique contribution to the field.

Numerous patents covering methodologies, hardware systems, and software algorithms directly related to monitoring, predicting, and controlling battery health are currently available for lithium-ion battery management systems and related diagnostic and prognostic tools. We aim to discover relevant patents and examine any possible overlaps by reviewing the state of intellectual property. Three essential patents pertinent to our project are discussed and outlined below, along with our strategy for avoiding infringement.

*A. **Patent Number 1 - US7576545B2: Lithium-ion battery prognostic testing and process***

The inventors of this patent were Harmohan N. Singh and James S. Johnson. The patent was granted in August 2009 and will be described in the sections below:

1) Summary

The patent outlines a strategy for determining the total capacity and predicting a lithium-ion battery's end-of-life (EOL). It does so by partially charging or discharging it and using open-circuit voltage (OCV) measurements before and after the process. The method calculates the state of charge (SoC) from these OCV values and correlates changes in SoC with the energy required for charging or discharging. The battery's total capacity can be estimated by extrapolating from the partial charge or discharge. The system also monitors the battery's capacity over time and uses trend analysis to forecast its EOL, providing a clear picture of its health.

Additionally, the invention describes a system for implementing this method, which includes an instrumentation module with sensors and a computer that processes the OCV data to predict battery life. The system integrates current sensors for measuring charge/discharge cycles and uses software tracking capacity trends over time, offering a proactive approach to battery management. The patent also discusses how this method can be used in various diagnostic tools, helping to ensure that lithium-ion batteries are monitored and maintained effectively throughout their lifecycle.

An illustration of an exemplary system used for determining the end-of-life (EOL) and capacity of a lithium-ion battery is presented in the figure below.

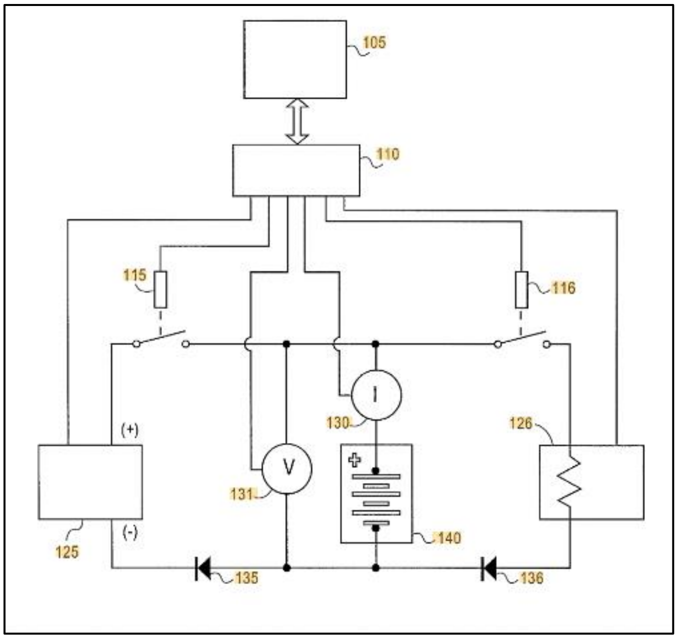


Fig. 12: An exemplary system for predicting the EOL of a lithium-ion battery.

2) Claims Summary

The patent has a total of 4 claims, but the ones that are directly related to our project include:

- A control module, depolarizing devices, sensors for measuring capacity and voltage, and a computer that predicts battery life through trend analysis
- A system that involves measuring open circuit voltages, tracking the change in state of charge, and tracking the battery's capacity over time to perform trend analysis to predict its end-of-life

3) Non-infringement

Our approach seeks to use different metrics to prevent infringement on this patent. We shall refrain from using direct open-circuit voltage (OCV) measurements for prognostic testing. Instead, we will concentrate on powering our machine-learning algorithms with continuous state-of-charge data. Instead of focusing on past data and OCV-based statistical techniques, focus on real-time learning models. Furthermore, we will ensure that the hardware and algorithms we create provide an apparent enhancement over or substitute for the particular charge/discharge cycle-based testing approach outlined in the patent.

*B. **Patent Number 2 - US10371753B1: Methods for online estimation of battery capacity and state of health***

The inventors of this patent were Shuoqin Wang, John Wang, Souren Soukiazian, and Jason A. Graetz. The patent was granted in August 2019 and will be described in the sections below:

1) Summary

This patent presents a method for real-time monitoring and estimation of battery capacity and state of health (SOH), specifically for metal-ion batteries like lithium-ion. The process involves correlating the open-circuit voltage (OCV) with the state of charge (SOC) for both anode and cathode. The method uses lookup tables, graphs, or equations to predict battery capacity by tracking voltage differences during battery operation. Additionally, it includes a nonlinear curve minimization technique (like Nelder-Mead) to improve capacity estimates over the battery's life and predict future capacity degradation.

The system continuously updates based on real-time data, allowing for battery management adjustments to optimize efficiency. This patent also introduces techniques and methods for predicting future battery capacity and health, enabling better battery life management through data-driven insights. The focus is primarily on real-time adjustments and voltage-based predictions rather than long-term trend analysis.

A chart [100] that shows a simplified schematic of an exemplary computer system for estimating a battery's capacity (based on several factors like voltage difference charge) is shown below:

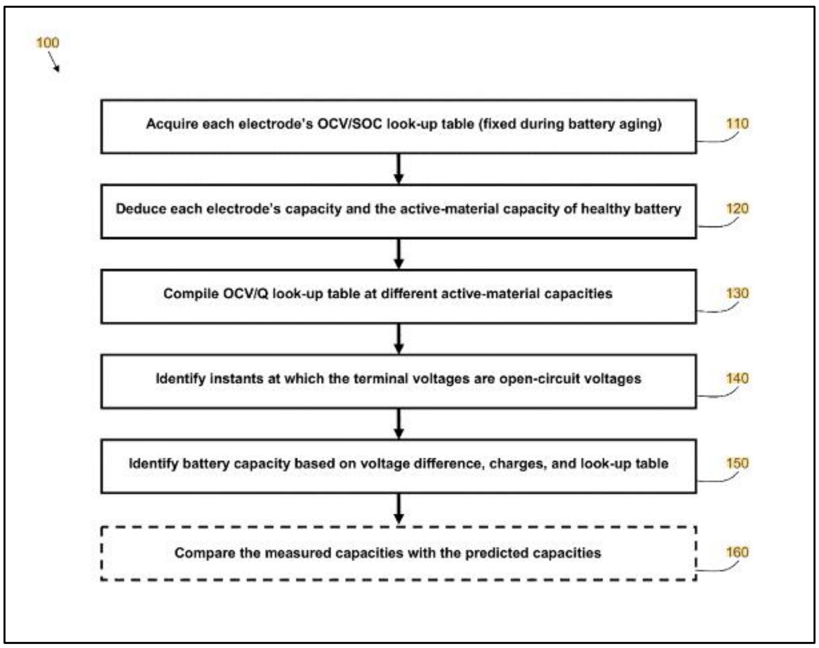


Fig. 13: A flowchart of online battery capacity estimation.

In the chart provided, the first three steps ([110], [120], [130]) are performed at the beginning of the battery's life. Then, the preceding two steps ([140], [150]) are implemented to estimate the battery's capacity. [160] compares the measure's capacities with the predicted ones, aiming to evaluate the used method.

2) Claims Summary

The patent has a total of 16 claims, but the ones that are related to our project include:

- A strategy for battery management comprised of real-time monitoring of the battery's capacity, state of health, and open-circuit voltage
- A method that utilizes the battery's capacity calculations and estimates how the capacity will evolve. This then provides a predictive model that showcases how the battery's lifespan and general performance

3) Non-infringement

This patent prioritizes real-time capacity estimation and open-circuit voltage data, which our project doesn't lean toward. Our method involves a long-term trend analysis, whereas the patent utilizes lookup tables and curve minimization for real-time monitoring. We are also focusing on developing a graphical user interface and backend system to visualize different features of the battery's performance, a functionality not addressed in the patent.

C. ***Patent Number 3 - US9465077B2: Battery health monitoring system and method***

The inventors of this patent were Corey T. Love and Karen Swider-Lyons. The patent was granted in October 2016 and will be described in the sections below:

1) Summary

This patent describes a system and method for monitoring a battery's condition using impedance spectroscopy. The technique outlined in the patent focuses on measuring the impedance response at different states of charge (SoC) within the prescribed voltage window of the battery by applying a frequency sweep utilizing either AC or voltage fluctuation. The battery's general state is then evaluated using this impedance response.

The idea of a precision frequency—the frequency at which the impedance values stay constant across all states of charge—makes this patent original. The system may apply a perturbation at this precise frequency and record the subsequent impedance response by locating this precision frequency. This frequency's impedance measurements are beneficial for determining the battery's state of health. Battery classification zones are a concept that the invention proposes. The impedance value of a battery can be classified into predefined categories to help identify its state of health (SOH) and diagnose problems, including deterioration, resistance changes, or overall performance decline.

Additionally, the patent includes a description of a battery health monitoring system. This system comprises a classification module, a precision frequency determination module, and impedance spectroscopy equipment. The impedance spectroscopy apparatus handles the frequency sweep and data collection on the impedance response. After processing this data, the precision frequency determination module determines the frequency at which impedance values remain constant for all charge states and applies perturbations. The classification module compares the impedance response at this frequency to previously defined zones to classify the battery's health.

To outline the process of monitoring the health of a battery using the method of impedance spectroscopy, a flow chart [100] that is broken down into four steps is shown below:

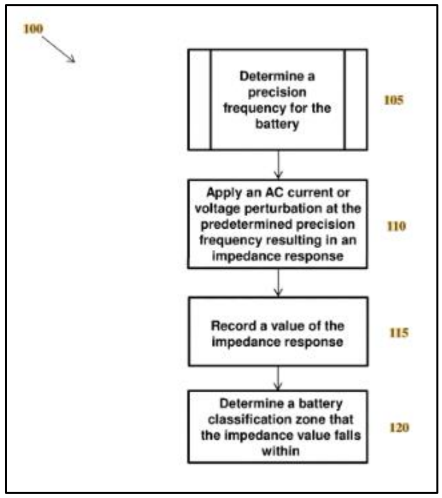


Fig. 14: A flow chart illustrating a diagnostic method for determining the battery health

The first step in the flow chart is to determine the precise frequency at which the battery's impedance values remain nearly constant during different charging phases [105]. Once the frequency has been determined, the battery is exposed to an alternating current or voltage [110]. In response to this disturbance, the battery exhibits a measurable impedance [115], which is noteworthy because it offers an essential statistic for further research. The recorded impedance value [120], which places the battery in a particular zone, can be used to evaluate the overall health of the battery as well as its state of charge (SoC) and state of health (SoH).

2) Claims Summary

The patent has a total of 17 claims, but the ones that are most related to our project include the following:

- A technique that uses impedance spectroscopy, records impedance values, and determines a classification zone to help monitor battery health by selecting a precision frequency

3) Non-infringement

Our project focuses on Li-ion battery diagnostic and prognosis testing and incorporates a range of methodologies, such as partial charge, depolarization, and SoC measurements. These techniques fundamentally differ from those described in the patent, which uses accurate frequency determination and impedance spectroscopy to evaluate battery health. Our method for diagnosing battery health does not include impedance spectroscopy or AC/voltage perturbations at a particular frequency. Instead, our approach departs from the scope of the patent by tracking the battery's condition over time utilizing a range of trend analysis methods. In addition, a front-end and back-end application is being developed by us to visualize the data collected from our testing procedures. This interface lets users track the battery's health, life, and charge level in real-time and receive actionable insights. A significant distinction from the patent in question is this software feature, especially the user interface and cloud integration parts.

D. ***Team Name***

For the name of our team, we have chosen the name Li-Logic. This name reflects our focus on lithium-ion battery technology while emphasizing our commitment to logical and innovative solutions in predicting battery capacity and lifespan. The name effectively captures the essence of our project and resonates with both the technical and scientific aspects of our work. We have conducted a thorough search to ensure that "Li-Logic" does not conflict with existing trademarks, allowing us to establish a unique identity for our team and project. This will facilitate collaboration and communication while protecting our intellectual contributions as we develop and innovate within the field of battery technology.

E. ***Team Contract***

1) Team member's obligations

As part of the Li-Logic team, each member has specific commitments that ensure the success and integrity of our project, which is focused on predicting the end of life for lithium-ion batteries. The obligations of the team members are outlined as follows:

- **Active participation:** Each member is expected to engage in team discussions and collaborative work sessions actively
- **Task accountability:** Every team member will be assigned specific roles and assignments aligning with their skills, expertise, and interests. Assignments are meant to be dealt with by their respective established deadlines
- **Communication:** Team members must communicate any challenges they encounter and provide frequent updates on their end of the project. Transparency and respect are vital for team cohesion
- **Intellectual property awareness:** Team members must understand and adhere to the guidelines regarding the protection and ownership of intellectual property created during the project, ensuring that all contributions are appropriately documented and attributed

2) Team member expulsion

Li-Logic reserves the right to expel a team member if their actions violate the agreed-upon team principles. Expulsion will only be considered under specific circumstances, jeopardizing the team's work, integrity, or cohesion. These circumstances include:

- **Failure to meet obligations:** If a team member consistently fails to complete assigned tasks by the agreed-upon deadlines without providing a valid reason or without prior communication to the team, they may be considered for expulsion. This includes a lack of meaningful contribution or engagement in the project
- **Breach of Confidentiality:** Unauthorized disclosure of proprietary project information, intellectual property, or confidential data, whether intentional or through negligence, will be grounds for immediate expulsion. Team members are required to protect sensitive information as outlined in the project's confidentiality terms
- **Unethical Conduct:** Any conduct that violates ethical research and development practices, such as falsifying data, plagiarism, or any activity that could harm the reputation or legality of the team, will result in immediate consideration for expulsion

- **Lack of Communication and Participation:** If a team member fails to communicate or attend team meetings for an extended period without explaining, the team may review their ongoing participation in the project. Continuous lack of involvement may signal withdrawal of interest and lead to expulsion

F. Intellectual Property Contract

The following Intellectual Property Contract is written solely for purposes of fulfilling the requirements of the undergraduate class ‘Senior Design I & II’ and does not reflect an actual IP agreement between contracted members (i.e. undergraduate students) of the project team. Any project deliverables and/or subsequent IP developed under this project is considered property of the Energy, Power, Sustainability, and Intelligence (EPSi) group and is bound by the CONFIDENTIALITY AGREEMENT signed on September 13, 2024, between the ‘Company’ (EPSi), and the contact(s) (Franko Sanabria, Jacob Stafford, Joshua Natal, Roberto Valdes, and Sebastian Munoz).

By providing initials below, the ‘contact(s)’ understand and agree to the above statement:

Print Name: Franko Sanabria,

Initials: Initial FS

Print Name: Jacob Stafford,

Initials: Initial JS

Print Name: Joshua Natal,

Initials: Initial JN

Print Name: Roberto Valdes, Initials: Initial RV

Print Name: Sebastian Munoz, Initials: Initial SM

The Li-Logic team IP contract defines the ownership, responsibilities, and decision-making processes related to the intellectual property (IP) created during the project. The contract ensures that contributions are recognized fairly, and the handling of IP rights is transparent and mutually agreed upon.

1) Criteria for co-inventorship

As part of the Li-Logic team, each member has specific obligations that ensure the success and integrity of our project. The obligations of the team members are outlined as follows:

- **Team Members:** Any team member who provides significant technical or creative input directly leading to the product's innovation (or invention) will be considered a co-inventor. Contributions such as theoretical development, design architecture, implementation of unique features, and even meaningful suggestions will be recognized
- **Mentors and Sponsors:** External mentors and sponsors will be recognized as co-inventors if they contribute to the core invention through hands-on participation or intellectual input that goes beyond standard advising
- **Extent of Involvement:** Each co-inventors involvement will be assessed based on their direct role in the invention process, including research, testing, or critical input that leads to original outcomes

2) *Invention spokesperson*

The team will designate a spokesperson as the primary representative for all matters related to the invention and its intellectual property. The spokesperson will:

- Serve as the main point of contact for patent filings, negotiations, and licensing agreements
- Represent the team in discussions with external parties such as investors, companies, or legal advisors
- Coordinate communications and ensure that all decisions made on behalf of the team are fair and transparent
- For the Li-Logic team, the spokesperson role will initially be assigned to Franko Sanabria, and any changes to this role will require team consensus.

3) *Profit distribution*

Profits generated from the intellectual property's commercialization, licensing, or sale will be distributed among the co-inventors based on their contribution to the project. The team will agree upon the method of distribution, which is initially proposed as follows:

- **Equal Distribution**: Since all members are expected to contribute meaningfully to the invention, each member will receive an equal share of profits.
- **Performance-Based Adjustments**: If certain members contribute significantly more, the team may adjust profit distribution based on effort and time commitment.

4) *Intellectual property decision-making*

Decisions regarding intellectual property and how said decisions will be made will follow a structured mechanism:

- **Consensus-Based Voting**: Major IP decisions require a majority vote from all co-inventors. Decisions about whether to patent, sell, or license the IP must be supported by at least 3 out of the 5 members of the team
- **Dispute Resolution**: If the team cannot reach a consensus, a mediator (such as the team's mentor) will be brought in to facilitate a fair discussion. The mediator’s recommendations will serve as a guide to help the team reach a final decision

In conclusion, the Li-Logic team's approach to intellectual property protection ensures that all aspects of the project, from the innovation process to patent strategy, are legally and ethically sound. We have carefully outlined our co-inventorship criteria and patent filing strategy, ensuring that the contributions of each team member are recognized relatively. Additionally, we have implemented transparent processes to manage intellectual property decisions, profit-sharing, and invention representation, providing a balanced and transparent foundation for future innovations.

Moreover, the Li-Logic team is committed to respecting existing patents and trademarks in the Li-ion battery industry. Thorough research has been conducted to avoid infringement on existing intellectual property rights, ensuring that our project is original and legally protected. By adhering to these frameworks, we aim to safeguard the team's innovations while fostering collaboration and maintaining compliance with industry standards.

This comprehensive intellectual property strategy is a robust safeguard for our inventions, ensuring that our research and development are adequately protected, and positions Li-Logic for success in future commercialization and technology ventures.

X. GLOBALIZATION

Globalization influences the design and implementation of everything, including our Battery Management System. Globalization impacts everything from regulatory compliance to user accessibility across international markets. Our goal is to develop a Battery Management System that can be deployed in many different countries worldwide, ensuring compatibility with local standards, global standards, and user requirements while meeting the expectations our future customers will expect from us. By focusing on a more universal-friendly design, we can quickly transition to international markets when ready.

A. Design for Global Accessibility and Compliance

Designing the Battery Management System with a global audience in mind requires you to make it simple and easily adaptable. Designing straightforward user interfaces and complying with international laws and regulations will make the BMS friendly to everyone. Our interface will use easy icons and visual elements like graphs to reduce reliance on language, making translating to different languages more accessible. For instance, by avoiding word-heavy information, we ensure that language translation is straightforward, does not confuse customers with mistranslations, and avoids the language barrier as much as possible. If needed, the BMS will comply with hazardous material regulations by following RoHS and REACH guidelines, including the battery Recycling program introduced by the WTO(11).

B. Trade Barriers and Regulatory Standards

Trade regulations and standards can be significant barriers to electronic products like a BMS in the international marketplace. To address these challenges, our BMS is designed to meet regulatory standards in major markets, including CE (Europe), UL (United States), and FCC (United States) certifications, along with certifications for hazardous materials compliance like RoHS (Restriction of Hazardous Substances) and REACH (Registration, Evaluation, Authorization, and Restriction of Chemicals) (12). Our product will start with these standards, and we can streamline the approval process for all countries while reducing compliance costs associated with entering new markets.

Our Battery Management System will also add customized features to specific regional needs. For instance, if a particular country needs to prioritize temperature tolerance because of its regional climate, we will adjust the temperature settings to be the first thing they see. Others may focus on data encryption and cybersecurity for battery data transmission, so we will focus on making a secure system.

C. Collaboration Tools for Global Development

Building a globally compatible BMS requires collaboration among a research team across different time zones and geographical locations. To support efficient and organized development, we used:

1) WhatsApp

Used to make group chats to ensure everyone is current on the project. They are used to share critical information across multiple devices and pin the most recent and relevant documents.

2) ***Microsoft Teams***

Facilitates regular team meetings with mentors, allowing screen sharing and interactive discussions on what they prefer and fixing issues that arise.

3) ***SharePoint***

It offers an easy way to document and divide up work. It also lets you have one primary and side document, so everything stays organized across multiple people and computers.

4) ***GitHub***

It gives the team leader control of our code and documentation, enabling team members to work asynchronously and stay on task. GitHub also allows us to track software changes and updates across the team, ensuring everyone is doing their part.

5) ***Reddit***

It offers a way to communicate with people from different countries and backgrounds. Allows for an open forum where anyone can communicate and share their findings.

These tools bridge the gap between team members and allow information collection to happen instantly. Using these tools makes the distance between team members and future customers irrelevant.

*D. **Consumer Feedback and Adaptation***

We conducted market research across different regions online via forums to ensure our BMS meets users' needs globally. We gathered feedback on essential features, data accessibility preferences, and operational requirements from electric vehicle owners, private battery bank owners, and mechanics. For instance, users in some regions prioritized monitoring the temperature due to varying temperatures from winter to summer. Some others focused on intuitive and straightforward data visualization or secure data transmission for remote monitoring to make it easier for the average person to understand.

In response to this feedback, our BMS includes customizable dashboards for real-time monitoring and support for multiple languages. We've also implemented data visualization tools that use universally understood metrics such as State of health, State of charge, and temperature indicators to accommodate users with different levels of technical expertise.

*E. **Ethical and Social Impact***

Our product's environmental and social impact will be noticed in a globalized world with a growing need for a good BMS. The BMS has been designed to be small and nonintrusive to limit the amount of waste used when it's no longer functional. The BMS supports global sustainability efforts by preventing premature degradation and ensuring longevity. Our goal is to minimize the environmental footprint of batteries in sectors like electric transportation and renewable energy without adding more to the waste when our product also becomes waste.

Additionally, the BMS aligns with ethical practices by ensuring data privacy and security for users worldwide. We protect user battery information from potential misuse by ensuring our product respects regional and global privacy laws.

*F. **Future of Global Battery Management***

As the global reliance on batteries grows—driven by electric vehicles, renewable energy storage, and portable electronics—the demand for advanced battery management systems becomes more critical. Our BMS is designed to be future-proof by allowing for seamless software updates and integration with more advanced machine learning that may help predict with higher accuracy.

By focusing on adaptability, international compliance, and a user-friendly design, our BMS is well-positioned to meet the growing needs of global markets. We aim to make our BMS a cornerstone of effective and responsible energy storage solutions worldwide through continuous refinement and responsiveness to international user feedback.

XI. STANDARDS CONSIDERATION

A product must meet the relevant industry standards to succeed in the market, as they ensure reliability, safety, and interoperability. Standards fall into three primary categories: De facto, De jure, and Voluntary Consensus (open) standards. Our battery diagnostic application must adhere to specific standards within the energy and diagnostics sector to ensure the product's functionality, safety, and user trust.

To bring our Li-ion battery diagnostic application to market, it must comply with relevant standards to ensure safe operation, interoperability, and reliability. This report section outlines vital standards we have identified as essential to our design, which will be instrumental in achieving compliance and ultimately influencing the project's success. These standards cover aspects of safety, quality, and performance, each with its criteria and requirements that guide the design and functionality of our application. Compliance with these standards will facilitate future commercialization and establish a robust, user-centered product. Below are the specific standards that our project will follow.

A. IEC 62133-2:2017 – Safety Requirements for Portable Battery Systems

The IEC 62133-2:2017 standard provides essential safety requirements for lithium-ion batteries used in portable applications. This standard is particularly relevant to our project as it addresses critical safety considerations, such as protection against overheating, overcharging, and potential electrical hazards—issues directly related to the operation of lithium-ion batteries in diagnostic settings. To comply with IEC 62133-2, we will integrate several protective features within our application, including automated shutdown mechanisms if dangerous conditions, like excessive heat, are detected. Our design will monitor battery conditions throughout diagnostic testing, ensuring that users are alerted if thresholds are crossed, thus minimizing risks associated with thermal runaway or battery damage. Additionally, the physical design will ensure adequate insulation and protective barriers to reduce electrical hazards, fully aligning with the safety criteria of IEC 62133-2. [11]

B. IEEE 1725 – Standard for Rechargeable Batteries for Mobile Phones

The IEEE 1725 standard focuses on quality, safety, and control protocols for lithium-ion batteries, particularly for portable electronics like mobile phones. Although primarily aimed at mobile devices, its battery protection, charge control, and system safety principles directly apply to our diagnostic tool. Ensuring our application complies with IEEE 1725 will allow us to integrate robust charge monitoring features that prioritize safe interactions with the battery system during diagnostics. For instance, our algorithms will be designed to track real-time voltage, temperature, and discharge rates, immediately halting testing if unsafe conditions are detected. This standard's battery cell protection and charge control guidelines offer us a reliable framework to build a stable and secure diagnostic system, preventing the likelihood of sudden malfunctions or long-term battery degradation. [12]

C. IEC 61000-4-2 – Electromagnetic Compatibility (EMC): Electrostatic Discharge Immunity Test

The IEC 61000-4-2 standard addresses the resilience of electronic devices to electrostatic discharge (ESD), which can disrupt sensitive systems like battery diagnostics. Since our application will likely be used in environments where static discharge is expected, following this standard is essential for ensuring reliable and stable operation. Our design will incorporate ESD-protective elements such as grounding mechanisms and shielded components to achieve compliance, reducing the risk of system malfunction due to ESD. Additionally, we will perform simulated static discharge testing to verify the application's ability to withstand typical ESD levels without compromising accuracy. This immunity to ESD will enhance the overall reliability of the diagnostic tool, ensuring that it can perform consistently in diverse and potentially disruptive environments. [13]

D. IEEE 7001-2021 – Standard for Transparency of Autonomous Systems

IEEE 7001-202 provides guidance on fostering transparency in AI-based decision-making, critical for building user trust in diagnostic systems. In the context of our battery diagnostic application, this standard helps ensure that the machine learning (ML) models used for diagnostics provide outputs that users can interpret and trust. Following IEEE 7001-2021 means designing the system to communicate predictions, including confidence levels, limitations, and explanations for specific recommendations. For instance, if a model flags a battery as degraded, the application can explain the key indicators contributing to this diagnosis, such as reduced capacity or abnormal discharge patterns.

The standard also encourages measures to assess and mitigate potential biases, such as evaluating model performance across different battery categories to ensure fair and accurate predictions. Our application enhances transparency and trustworthiness by adhering to IEEE 7001-2021. It offers users a clear, educational experience that explains how diagnostic insights are generated, setting realistic expectations and improving user engagement with the system. [14]

In summary, our project will adhere to the standards IEC 62133-2:2017, IEEE 1725, IEC 61000-4-2, and IEEE 7001-2021 to ensure that our Li-ion battery diagnostic application meets the highest standards of safety, reliability, and quality. Each standard selected aligns closely with the needs of our project, from battery protection and user safety to immunity against electrostatic interference and user engagement. By implementing these standards, we commit to delivering a diagnostic tool well-suited to battery testing and management demands while prioritizing user safety and maintaining compliance with industry expectations.

XII. Health and Safety

Environmental health and safety are critical to designing and managing our Battery Management System if we want it to enter international markets. By integrating sustainable practices and following global regulations, we will prioritize the health of users and our team's safety while minimizing the environmental impact. Also provided with the BMS will be a step by step guide showing how to fix and properly dispose of each part of the system.

*A. **User Health and Safety***

Our BMS is designed with features that protect users while still giving them all the features that they want. A list of some of the things we do to help users and the environment:

- **Sustainable Materials**: The BMS incorporates recyclable materials reducing waste and supporting greener economy principles.
- **Energy Efficiency**: Optimized power management ensures minimal energy consumption reducing the system's carbon footprint.
- **Hazard Prevention**: RoHS-compliant components eliminate harmful carcinogenic substances like lead and cadmium.

*B. **Team Environmental Health and Safety***

During the development process, our team follows best practices to ensure safety and sustainability:

- **Material Safety**: All materials are handled carefully, using appropriate PPE to prevent exposure to harmful substances and ensure proper waste disposal.
- **Sustainable Workspaces**: Development is conducted in energy-efficient environments with proper ventilation, lighting, and recycling facilities to support green practices.
- **Eco-Conscious Sourcing**: Suppliers are selected based on their adherence to sustainable and environmentally friendly practices. Showing that they care about the environment matters.

*C. **Liability and Foreseeability***

We address potential risks and liabilities through proactive planning and adherence to global standards:

- **Environmental Risk Assessments**: Comprehensive evaluations are performed during all phases to identify and mitigate risks associated with production and operation.
- **Compliance with Standards**: The BMS adheres to international standards like RoHS and ISO 14001, ensuring it meets strict safety and environmental guidelines locally and internationally.
- **Lifecycle Management**: The system includes a guide for proper recycling and disposal, minimizing its environmental footprint at the end of its lifecycle. There will be documentation at every step so you will know what each part comprises and does.

Our commitment to environmental health and safety is embedded in our BMS's design, development, and implementation. By prioritizing sustainability and compliance, we deliver a product that meets user needs and contributes positively to global environmental goals. Looking ahead to possible liability helps us approach the design in a more future-friendly way, giving us a clear and bright path forward.

XIII. Environmental Considerations

As engineers, we must take steps to ensure that the products we create are sustainable, environmentally conscious, and manufacturable without creating unintended consequences. This section aims to detail how our Battery Diagnostic and Prognostic Tool Application will be developed to have a minimal impact on the environment by sustainability initiatives like using RoHS components when using hardware, creating a design that can be easily taken apart and repaired, considering LCIs (Life Cycle Impacts) in any components we select, and as a whole, how our team will comply with the sustainable design guidelines established by the Hannover Principles.

A. *Using RoHS Components*

Although our project is mostly software-based, we must use RoHS-compliant components where available in our design. This is done so that none of our hardware contains substances such as lead, cadmium, hexavalent chromium, mercury, and various flame retardants considered "hazardous" substances for the environment and a reasonable waste handling procedure. Using RoHS components helps to promote environmental and safety conditions for our users.

- Health & Safety Protections: By eliminating toxic substances found in some electronic components, RoHS compliance promotes environmental protection and improves the safety of users and manufacturers.
- Sourcing Standards: We have sourced our components from verified suppliers after coordinating with our sponsor. This helps ensure we comply with environmental regulations while maintaining high-quality standards for our tool's hardware.

B. *Designing for Easy Disassembly*

Making our diagnostic tool easy to assemble and disassemble helps expedite both manufacturability and recyclability. Easy disassembly enables faster and cheaper repairs, component replacement, and, at the end of life, recycling.

- Manufacturability: The modular design of our tool helps support efficient production and can be easily integrated with legacy systems.
- Recyclability: Using components like the Raspberry Pi, battery modules, and a BMS, our design reduces e-waste and promotes responsible disposal at the end of the product's life.

C. *Component Selection Based on LCIA*

Our team has used the Life Cycle Impact Assessment (LCIA) to evaluate components and minimize their environmental footprint over the entire product lifecycle.

- Environmental Impact: Components are selected based on their energy efficiency and material sustainability, ensuring compliance with our focus on energy-efficient operation. They are also compared by how much energy they use, their carbon footprint, and the potential for the depletion of natural resources. The components with the least environmental impacts will be prioritized to create the most sustainable solution.
- Sustainability: Our approach helps to support the predictive maintenance goals of our tool, which reduces the premature replacement of batteries and the optimized use of resources. The result is a reduced ecological footprint within the industry.

*D. **Adherence to Hannover Principles***

Our project seeks to align itself as closely as possible to the Hannover principles, which outline some objectives for sustainable design. These principles help promote sustainability and our responsibility to the environment and highlight how interconnected humanity is with the natural environment. Here are three examples of how we are fulfilling these guidelines:

- Principle 5: Create Safe Objects of Long-Term Value

  Our tool's modular design and RoHS-compliant components make it easy to upgrade in the future and make it long-lasting and compatible.
- Principle 6: Eliminate the Concept of Waste

  Our tool minimizes battery waste and extends component lifespans by facilitating modular repairs and using machine learning to optimize energy usage.
- Principle 7: Rely on Natural Energy Flows

  To reduce its carbon footprint, our application leverages Azure cloud services fueled by renewable energy sources and can be readily integrated with renewable energy systems.

When creating our Battery Diagnostic & Prognostic Tool, environmental factors were considered. We show our dedication to sustainability and ecological responsibility by employing RoHS components, designing for easy disassembly, choosing components based on LCIA, and abiding by the Hannover Principles. This all-encompassing strategy guarantees that our tool is creative and effective and helps create a better world and a more sustainable energy future.

XIV. SUSTAINABILITY CONSIDERATIONS

Sustainability is crucial. It's key to ensuring that our Battery Prognostic and Diagnostic Tool stays effective and eco-friendly over time. So, we're focused on durability, energy efficiency, and keeping the hardware and software relevant. We aim to create something that cuts down on environmental harm while also packing in long-term value. These sustainability principles are the backbone of how we design and implement our project, ensuring it's a solid choice for anyone needing battery monitoring and diagnostics.

A. ***Hardware***

The first step in sustainability is to carefully choose components that have the least possible negative influence on the environment. The Raspberry Pi and sensors, among other hardware components, will be selected for the tool based on their potential for recycling and energy efficiency. We will give priority to the use of recyclable enclosures made of low-impact materials like plastic or aluminum, even though some components, such printed circuit boards (PCBs), are likely to add to e-waste. This lowers the hardware's overall carbon footprint by guaranteeing that it is both usable and recyclable.

Energy efficiency is a key factor in the tool's hardware design. By selecting low-power components and optimizing the design to minimize energy loss, we reduce electricity consumption, thus benefiting both the environment and the user. In the long term, this lowers operational costs while contributing to the tool's sustainability by ensuring its efficient operation over an extended period.

By utilizing premium, long-lasting materials, we also want to extend the Battery Prognostic and Diagnostic Tool's lifespan. To extend the product's lifecycle and minimize electronic waste, modular design will be used to guarantee that components are readily replaced or repairable. By encouraging consumers to fix malfunctioning parts rather than throw them away, this strategy lessens its negative effects on the environment and promotes a circular economy.

B. ***Software***

The same is true for software: efficiency is crucial. The creation of efficient algorithms that lower the processing power needed for machine learning predictions and real-time data analysis will be our top priority. This will improve the system's overall performance and reduce the Raspberry Pi's energy consumption. In addition to enhancing the tool's energy efficiency, effective software guarantees a more seamless user experience.

To promote cooperation and creativity, we also want to implement open-source software techniques. Open-source code makes it possible for the tool to be improved continuously over time, keeping it current and effective without the need for periodic hardware repairs. We'll give regular software upgrades to address bugs, add new functionality, and boost efficiency. We guarantee that the tool stays useful and current for years by providing simple-to-install upgrades, which reduces the need for product replacements.

By making these efforts, we guarantee the Battery Prognostic and Diagnostic Tool's durability and environmental responsibility. We can prolong the tool's lifecycle and help create a more environmentally friendly future by choosing sustainable hardware components, maximizing energy efficiency, and leveraging open-source software methods.

XV. MANUFACTURABILITY CONSIDERATIONS

Design for Manufacturing (DFM) is an essential practice that ensures our Battery Diagnostic and Prognostic Tool Application is not only innovative and functional but also efficient to produce at scale. By adopting DFM principles, we aim to create a tool that meets high standards of reliability and performance while remaining cost-effective and practical to manufacture. Early-stage design decisions will play a critical role in ensuring that our tool is simple to produce, integrates seamlessly with existing systems, and is accessible to end users and manufacturers alike. In this section, we have outlined the key principles we will follow to achieve these goals:

A. ***Simple Design***

A simplified design minimizes complexity, reduces costs, and improves reliability. Our Battery Diagnostic and Prognostic Tool will prioritize using a modular architecture with as few components as possible while still achieving high functionality. Each subsystem—such as the diagnostic sensors, battery management system (BMS), cloud system, and user interface—will be carefully evaluated to eliminate redundant elements.

For instance, instead of using separate sensors for every diagnostic parameter, we will utilize multi-function sensors capable of measuring multiple metrics such as State of Charge (SOC), State of Health (SOH), and temperature. This reduces the total number of parts required, streamlines assembly, and lowers the likelihood of manufacturing defects or system failures.

Additionally, the cloud-based architecture reduces the need for onboard computational hardware. The hardware design can remain lightweight and less complex by offloading heavy processing tasks, such as predictive diagnostics and advanced analytics, to cloud servers. This reduction in hardware complexity translates to fewer components, simpler assembly processes, and lower manufacturing costs.

B. ***Use of Common and Standardized Parts***

By leveraging common and standardized components, we will ensure the tool is easy to assemble and maintain. Standard parts, such as microcontrollers, diagnostic sensors, and connectors, will be selected to ensure compatibility with existing manufacturing processes and reduce production costs.

For example, the Raspberry Pi Pico, chosen for its advanced processing capabilities and cost efficiency, is widely used and readily available in the market. Similarly, the sensors for diagnostic data collection will be selected based on their compliance with established industry standards, such as ISO for battery management systems. This approach reduces lead times for part procurement and allows for scalability, making it easier for manufacturers to produce the tool in larger volumes without specialized equipment or training.

Additionally, cloud integration allows for future-proofing by enabling manufacturers to easily update software and algorithms, reducing the need for new hardware iterations. This extends the product's lifecycle and minimizes retooling costs for future production runs.

C. ***Leveraging Cloud Integration***

The integration of cloud technology not only enhances the functionality of our tool but also contributes to its manufacturability. Cloud services centralize data storage, processing, and user interface elements, reducing the need for high-capacity onboard computing hardware. This enables us to use cost-effective microcontrollers like the Raspberry Pi Pico for local processing while offloading computationally intensive tasks like trend analysis and prognostics to the cloud.

By reducing the complexity of onboard systems, we simplify manufacturing and assembly processes, as fewer components are needed for high-performance operations. Additionally, using a cloud platform minimizes the dependency on specialized hardware, enabling manufacturers to assemble the product using widely available, standardized parts.

*D. **Ease of Assembly and Sustainability***

Ease of assembly is emphasized through the modular design of subsystems. Components, such as the sensors and communication modules, are housed in user-friendly, snap-fit enclosures, minimizing the need for specialized tools or expertise during assembly. The cloud system also reduces the environmental footprint by enabling predictive maintenance. Manufacturers can use diagnostic data to preemptively address potential defects in components, ensuring quality control without additional testing infrastructure.

By emphasizing simplicity, leveraging the cloud and machine learning for streamlined manufacturing processes, and using standardized components, our Battery Diagnostic and Prognostic Tool Application is designed to be cost-effective, scalable, and innovative. These principles ensure that our product meets user needs while remaining practical and sustainable for manufacturers.

XVI. ETHICAL CONSIDERATIONS AND SOCIAL IMPACT

In engineering, there will always be projects that have the potential to raise ethical concerns or impact current societal norms. As such, engineers must uphold a code of integrity to ensure that their inventions and solutions comply with the ethical standards of society. There are engineering organizations of varying disciplines that represent engineers in the industry, and to promote good moral health among their members, there is typically a set code of ethics to guide decisions. For electrical and computer engineers, IEEE, or the Institute of Electrical and Electronics Engineers, prescribes their code of ethics, which contains principles that will be wholly relevant to our senior design project. [3] If the IEEE Code of Ethics cannot assist in solving an ethical dilemma, we will consult our team mentor, Dr. Arif Sarwat, and work with an ethical theory model.

A. ***Ethical Considerations***

Creating an application for battery diagnostics, especially one based on machine learning principles, can raise ethical concerns regarding its predictive capabilities. Since the tool relies on machine learning algorithms to make decisions about battery health, it is inherently susceptible to bias if the data the algorithm is trained on is not of a certain caliber. Such situations can arise where the tested battery type falls outside the range of data the algorithm has learned from, including various operational characteristics that can vary from one system to the next.

Suppose our algorithm is trained on the most popular brands of batteries, including typical scenarios in which they are used. This can create a bias in cases where the user intends to test a lesser-known battery, which could have different operational features, leading to unfair or inaccurate predictions. Thus, a particular ethical dilemma arises.

One of the most frequent ethical dilemmas in machine learning-based applications involves the disclosure of known biases or inaccuracies the model contains when creating predictions. This scenario is not directly addressed within the IEEE Code of Ethics, but given the rise of AI in recent years, there is a growing concern regarding these deficiencies. The need for cloud-based connections for synchronizing data can also compromise users' privacy since the battery data is considered sensitive and vulnerable. As such, users deserve to be adequately informed of how their data is handled.

There are four options to choose from regarding making the most ethical choice as soon as our team becomes aware of this issue:

1. Do nothing: Do not inform users of the potential bias within the model and refuse to address it.
2. Disclose the bias, but don’t take action to adjust the model: Let users know there are shortcomings in the model’s accuracy, but do not focus on improving the model. This choice could be made if the bias only affects a relatively small number of users or if there is difficulty in trying to fix the issue.
3. Disclose and mitigate the bias: Let users know there is a bias and immediately work towards fixing the model in future updates. This choice prioritizes being transparent with users while working to make the model more objective.
4. Fix the bias before informing the users: Proactively work to identify and mitigate any apparent biases before informing users.

With that established, the next stage involves analyzing the bias within the principles of four ethical theories:

1. Utilitarianism: This ethical theory model focuses on making an ethical decision to benefit the most people. That would mean making a decision that will align with the sentiment held by most users. However, if addressing the bias can improve the system's fairness without getting in the way of its performance, it would be best to mitigate it.
2. Ethical Egoism: This theory prioritizes the self-interest of the company or organization; it would involve trying to mitigate the bias if and only if the company's reputation is at stake. A short-term solution could prioritize the model's efficiency while preparing a longer-term solution if the issue affected the organization's interests.
3. Kantian Ethics: Kantian ethics focuses on whether an ethical decision would set a universal precedent, especially without contradiction. It bears the question of whether this decision would help improve future decisions. Ignoring the bias, for example, would fail to set a precedent that respects the users' interests.
4. Rights Ethics: Rights ethics centers on respecting users' rights, including their right to fair and unbiased predictions. More than the others, it would call for acting to fix the bias as soon as possible so that users are not disadvantaged when using the tool.

The following table highlights our group's options but in a more concise form. The subsequent table then assigns scores corresponding to each option against the four ethical theory models.

TABLE 17: LIST OF OPTIONS FOR ADDRESSING BIAS IN MACHINE LEARNING

Option	Description
1	Don't inform users about the bias, and don't adjust the model.
2	Inform users about the bias, but don't attempt to mitigate it.
3	Inform users about the bias and actively work to fix it.
4	Fix the bias before informing the users.

TABLE 18: ETHICAL THEORY SCORING OF OPTIONS FOR ADDRESSING BIAS IN MACHINE LEARNING

Options	Utilitarianism	Egoism	Kantian	Rights	Score
1. Do nothing	0	.75	.25	0	1
2. Disclose but don't fix	.25	.75	.5	.25	1.75
3. Disclose and mitigate	.5	.5	1	.75	2.75
4. Fix before informing	1	1	1	1	4

Based on these comparisons, Option 4, which entails fixing the bias before informing the users, appears to be the best option. This is because it respects users' rights, sets a positive precedent according to Kantian Ethics, and protects our team while benefiting most people.

B. ***Social Impact***

Our Battery Diagnostic and Prognostic Tool Application will open doors for users to explore a user-friendly experience that will provide insights into current battery performance and its expected outlook regarding overall battery health. Several benefits come to mind when creating this product to contribute to society. Namely, creating an easily deployable tool for real-time monitoring and predictive maintenance can significantly affect the environment. The battery's lifespan is extended by tracking the degradation of lithium-ion batteries; from a global perspective, this can substantially reduce waste and strain on battery production and disposal procedures. As for the individual user, being informed of these battery health metrics can allow for the more effective management of battery resources, leading to less frequent replacements over the long term.

There is also an economic impact; deploying this tool through cost-effective means, whether a PC application or an application on a microcontroller, would be accessible to many users, varying from hobbyists to professionals. As a result, the increased adoption of battery management technologies will promote growth within the sector and other industries that utilize batteries in their applications. The predictive maintenance features will also provide substantial cost savings for individuals and businesses.

Yet another factor in battery management applications is the notion of increasing safety. Focusing on generating accurate data and monitoring lithium-ion batteries in real time can have preventative implications, such as preventing fires or explosions related to battery failures. The connection to the cloud will also add a layer of security by informing the user of potential failures before they come to light.

This tool's benefits to a global audience will create a significant social impact and promote a vision of the good life. This is multifaceted, aiding users in promoting environmentally conscious habits, increasing cost savings over the long term, and ensuring safety for all involved.

XVII. CONCEPT DEVELOPMENT

Concept development for the Battery Prognostic and Diagnostic Tool aims to enhance battery maintenance and prolong life expectancy. Key constraints include the complexity of machine learning (ML) algorithms, transitioning to real-world applications, and managing data storage in both cloud and local environments. Ensuring efficiency in offline settings while maintaining seamless cloud integration and hardware compatibility for real-time control is critical.

A local development stack is essential for offline use, with plans for future cloud integration. Python libraries like Scikit-learn, TensorFlow, and PyTorch will enable the implementation of ML models, such as K-Means for clustering and neural networks for predicting battery lifespan and state of health. Data processing will utilize Pandas and NumPy, with model training possible on local devices like Raspberry Pi or in the cloud (AWS or Azure).

To enhance user accessibility, a web-based interface will be developed using Flask or Django, facilitating communication with ML models and allowing users to monitor battery health. Azure and AWS provide robust cloud integration, with Azure Machine Learning for model management and AWS S3 for data storage, complemented by Lambda and SageMaker for workflow automation.

Real-world validation will involve hardware-in-the-loop testing to replicate battery operations and refine the accuracy of ML and reinforcement learning algorithms. The final product will integrate these tools within a robust infrastructure for consistent monitoring and performance improvement across various operational environments.

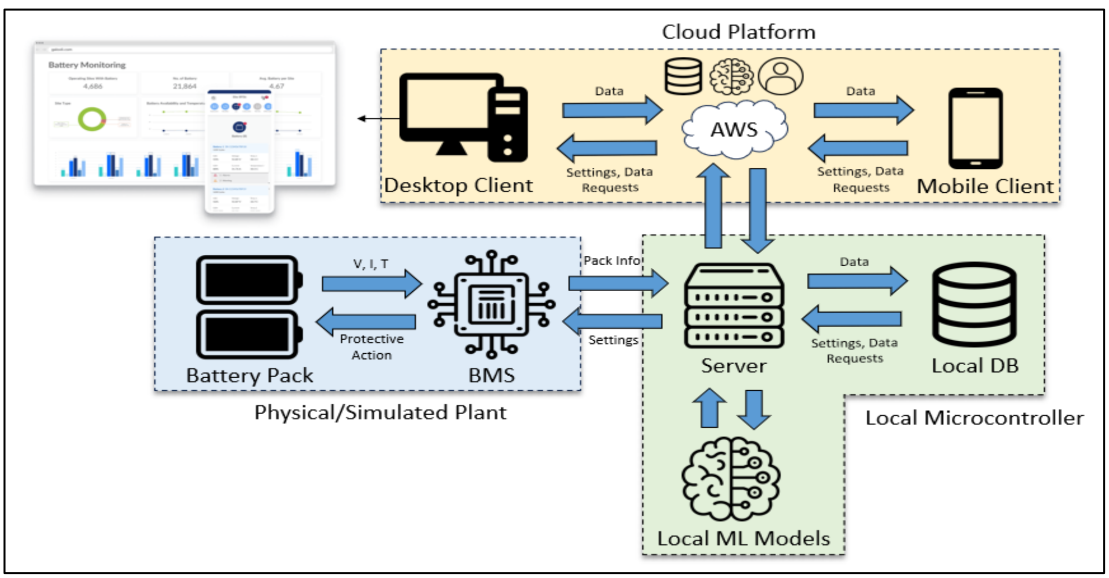


Fig 15: Battery Tool Deployment Overview [4]

To get a rigid idea of what we needed to construct, we referenced the Battery Tool Deployment Overview (Fig. 13) that the sponsor gave our team. A battery pack and a BMS are everything physically provided. Then, we must design a server, an ML model, and a user interface and send everything to the cloud. Using that as a basis for a design will mean we need to focus on three main groups:

- The server, which is hardware.
- The ML model is going to sort the data.
- The user interface is what is going to be used by the average user.

A. ***Alternative Options***

1) Option 1: Random forest algorithm, Flask interface, and AWS cloud service

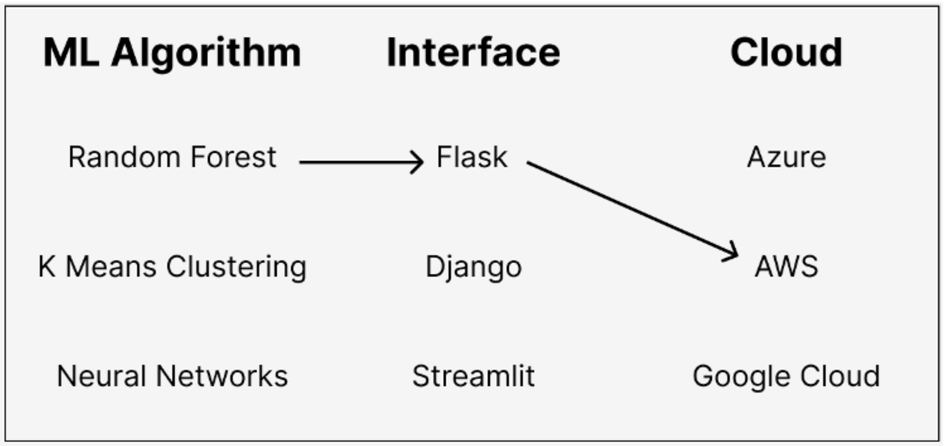


Fig. 16: Concept combination option 1

a) Advantages

- Handles large datasets with high accuracy
- Robust against overfitting
- Easiest to interpret results

b) Disadvantages

- Does not handle datasets with high dimensionality well
- ML algorithm is not as effective at sorting data
- May require significant tuning for optimal performance

2) Option 2: K-means clustering algorithm, Streamlit interface, Google Cloud service

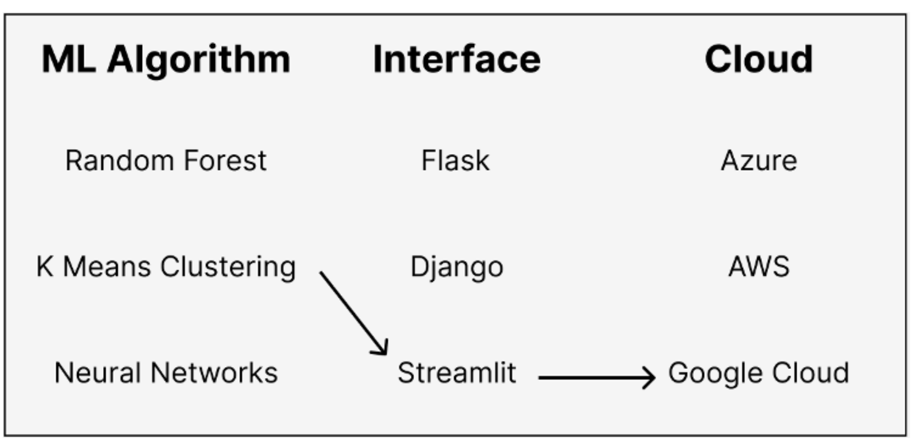


Fig. 17: Concept combination, Option 2

a) Advantages

- Simple and efficient for clustering tasks
- Easy to implement and visualize results
- Lightweight

b) Disadvantages

- Least accurate among the designs
- Requires a pre-defined number of clusters

3) *Option 3: Neural networks algorithm, Flask interface, and Azure cloud service*

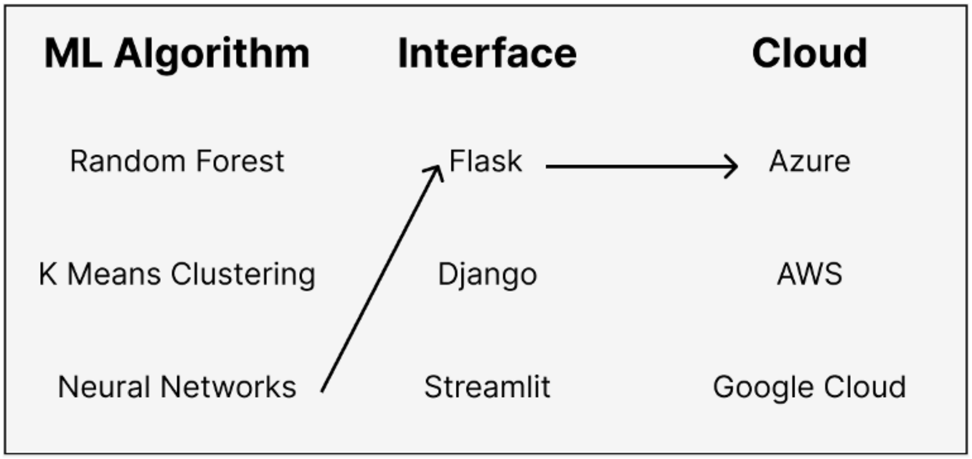


Fig. 18: Concept Combination, Option 3

a) Advantages

- Capable of handling complex relationships in data
- Flexible and scalable
- Supports large datasets and multi-dimensional data
- Azure integrates easily with Flask and TensorFlow ML models

b) Disadvantages

- Longer training times
- Requires more expertise to set up and maintain

TABLE 19: TABLE OF RELATIVE IMPORTANCE

	Cost	**Quality**	**Accuracy**	**Ease of Use**	**Size**
Cost	1	1	3/5	3/5	1/3
Quality	1	1	3/5	3/5	3
Accuracy	5/3	5/3	1	1	5
Ease of Use	5/3	5/3	1	1	5
Size	1/3	1/3	1/5	1/5	1

TABLE 20: TABLE OF WEIGHTS USED TO SCORE DIFFERENT FEATURES OF THE BATTERY DIAGNOSTIC DEVICE.

	Cost	**Quality**	**Accuracy**	**Ease of Use**	**Size**	**G mean**	**W**
Cost	1	1	.6	.6	.33	.65	0.12
Quality	1	1	.6	.6	3	1.02	0.19
Accuracy	1.6	1.6	1	1	5	1.67	0.31
Ease of Use	1.6	1.6	1	1	5	1.67	0.31
Size	.33	.33	.2	.2	1	0.34	0.06
					Total	5.35	

To help assist with choosing the best option for this project, we rated the importance of each feature. Our team weighed each feature based on our group and project constraints—all the levels of importance are listed in Table 1, with the weights listed in Table 2.

TABLE 21: TABLE OF ALL THE WEIGHTS COMPARED TO EACH PROJECT.

Objectives	**W**	**Option 1**		**Option 2**		**Option 3**	
Cost	0.12	4	.48	2	.24	5	.6
Quality	0.19	2	.38	4	.76	3	.57
Accuracy	0.31	2	.62	5	1.55	3	.93
Ease of Use	0.31	4	1.24	3	.93	5	1.55
Size	0.06	3	0.18	2	0.12	4	0.24
Totals			2.9		3.6		3.89

This solution ensures high scalability and adaptability across different operational environments by leveraging neural networks for complex diagnostics, Flask for flexible and lightweight user interaction, and Azure for seamless cloud integration. As the tool undergoes continuous testing and validation through hardware-in-the-loop simulations, we will refine its accuracy and performance, paving the way for deployment in real-world battery systems. This approach will significantly enhance battery life management, offering users a powerful, efficient, and accessible tool for predictive maintenance and diagnostics.

XVIII. END PRODUCT DESCRIPTION AND OTHER DELIVERABLES

This section details the proposed battery diagnostic and prognostic tool application, including its type, implementation process, contents, and various components that will help both developers and users understand the system and start suggesting potential solutions. The implementation section explains the motivation behind developing this tool and its intended functions post-development, focusing on fulfilling user needs. The design is based on rational planning aimed at meeting these requirements effectively.

The system architecture encompasses critical subsystems like the battery management system (BMS), diagnostic sensors, user interface, and cloud-based services that provide further analytical power. The BMS collects data from the battery regarding its state of charge (SoC), voltage, and temperature, while diagnostic sensors track performance trends, such as internal resistance or capacity degradation. Cloud integration stores diagnostic data runs predictive models and generates reports or alerts based on battery health. The user interface enables users to easily interact with and monitor battery status, set parameters for diagnostic testing, and receive updates or recommendations.

This multi-layered approach allows users, engineers, or service providers to monitor battery performance over time and predict failures or necessary maintenance, optimizing battery lifespan and safety.

A. End Product Description

The battery diagnostic and prognostic tool integrates advanced methods for monitoring and analyzing lithium-ion batteries. Utilizing techniques such as depolarization, partial charging, state of charge (SoC) measurements, and trend analysis of battery capacity, the tool aims to provide accurate diagnostics and predictive capabilities for battery health and performance. This section details the primary system components and their interactions, helping visualize the operational flow.

The Level 0 high-level block diagram in Fig. 19 presents the system's core elements, including sensors for data collection, power supply, user interface, central processing unit, and output displays for diagnostic results. It outlines the data flow from input to output, offering a clear overview of the system's operation.

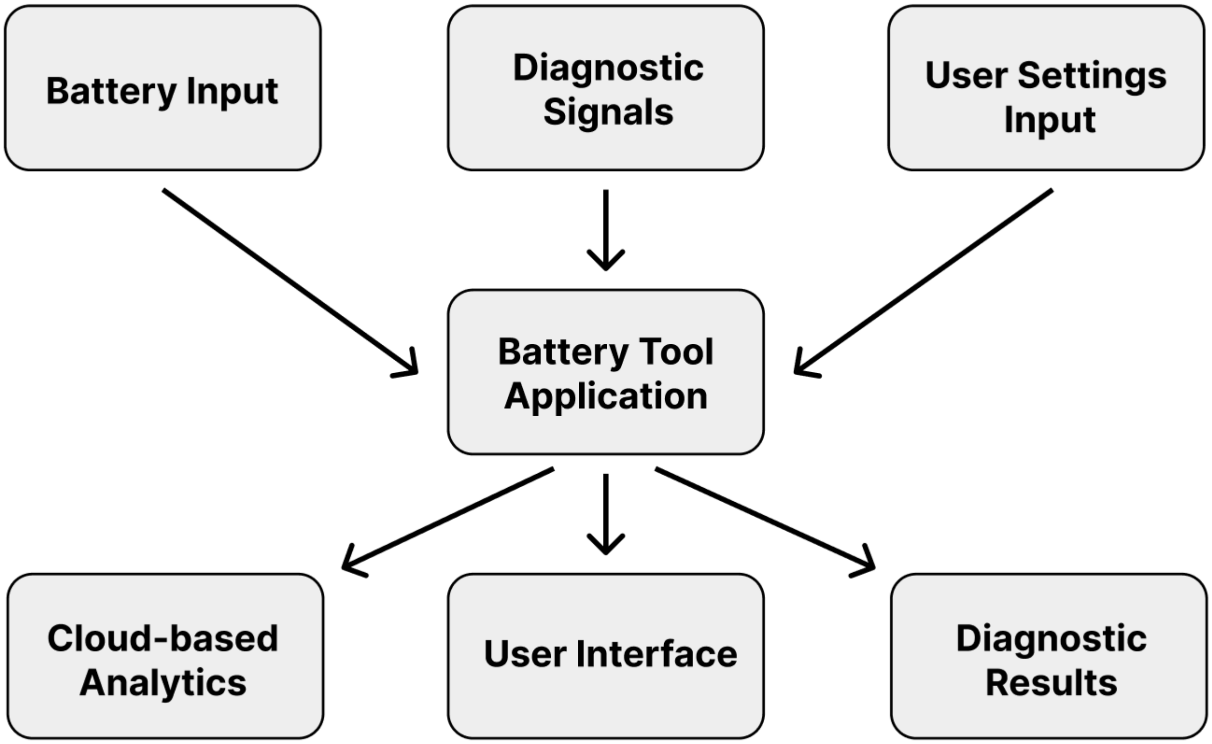


Fig. 19: Level 0 block diagram of the battery diagnostic and prognostic tool application

Table 22 outlines the core functionalities of the battery diagnostic tool application at a high level. It lists the primary inputs and outputs, along with a brief description of their functionality; this provides a clear understanding of the fundamental operations of the application, highlighting how the system processes battery signals and interfaces with the user.

TABLE 22: LEVEL 0 FUNCTIONALITY OF THE BATTERY DIAGNOSTIC AND TOOL APPLICATION

Inputs	Outputs	Functionality
Battery data (voltage, current, temperature)	Diagnostic reports, cloud-based analytics	Collects battery data and runs diagnostics using ML models
Diagnostic signals	Prognosis and Trend Analysis Health	Data used for machine learning models to make predictions
User settings input	Diagnostic results and health predictions	Allows user customization of diagnostic parameters

The main subsystems include the diagnostic sensors, battery management system (BMS), cloud system, and user interface. Each subsystem interacts to ensure the tool functions correctly and efficiently. The following section delves into these subsystems in more detail.

The Level 1 block diagram in Fig. 19 presents a comprehensive overview of the Li-ion battery diagnostic system, breaking it down into its primary subsystems: diagnostic sensors, battery management system (BMS), cloud system, and user interface. This diagram shows the interaction between these subsystems. The power supply provides stable voltage to all components. The BMS gathers and forwards battery data to the diagnostic sensors and cloud system. The diagnostic sensors analyze parameters like internal resistance, sending results to the cloud. With data storage and machine learning, the cloud system processes this information to generate predictive insights displayed on the user interface. The UI allows users to monitor status, receive alerts, and control settings, creating a responsive feedback loop.

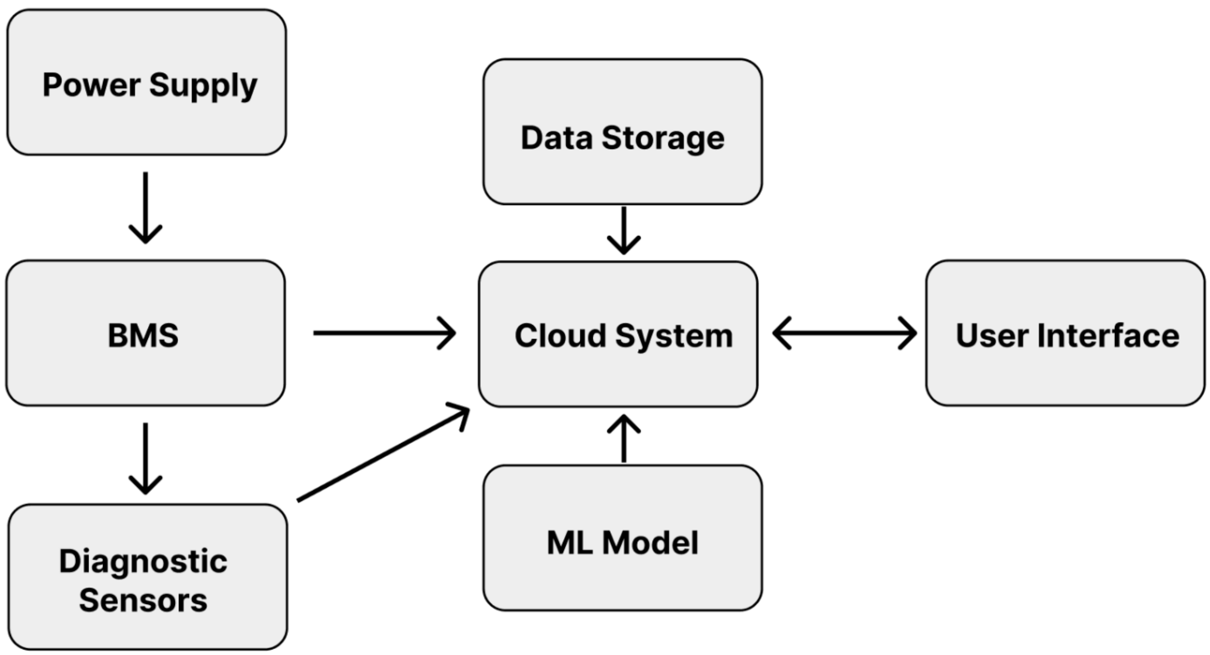


Fig. 20: Level 1 block diagram of the battery diagnostic and prognostic tool application

Table 23 provides a comprehensive overview of the specific functionalities of each subsystem within the battery diagnostic and prognostic tool. It lists the inputs and outputs for each subsystem and describes their roles in the overall system. This detailed breakdown clarifies how each subsystem contributes to analyzing battery health, performing diagnostic checks, and predicting potential failures. Additionally, it highlights the role of the user interface in displaying diagnostic data and the cloud integration that facilitates remote monitoring and data processing, ensuring an efficient and user-friendly experience.

TABLE 23: LEVEL 1 FUNCTIONALITY OF THE BATTERY DIAGNOSTIC AND TOOL APPLICATION

Subsystem	Inputs	Outputs	Functionality
Battery management system (BMS)	Battery parameters (voltage, temperature, SOC)	Data to cloud and diagnostic system	Collects battery performance data and sends it to the cloud for processing
Diagnostic sensors	Internal current, voltage, temperature	Raw data for diagnostic analysis	Gathers additional diagnostic signals
Cloud system	Raw battery data, diagnostic signals	Cloud-based analysis, trend predictions	Runs machine learning models to predict battery life and failure, stores data
User interface	User input (e.g., diagnostic mode, settings)	Display data, alerts, diagnostic reports	Provides a visual interface to interact with the system, manage settings, and view results

B. Functions

The Li-ion battery diagnostic and prognostic tool has multiple functions to enhance usability and ensure reliable battery monitoring and predictive analysis. These functions are implemented through the interaction of subsystems, each contributing to the overall performance and user experience. This subsection outlines how these functions are performed and explains the role of each subsystem.

Fig. 21 shows the diagnostic sensor subsystem, detailing how battery parameters are measured for real-time assessment. This includes temperature, voltage, and current sensors that collect data for in-depth diagnostics.

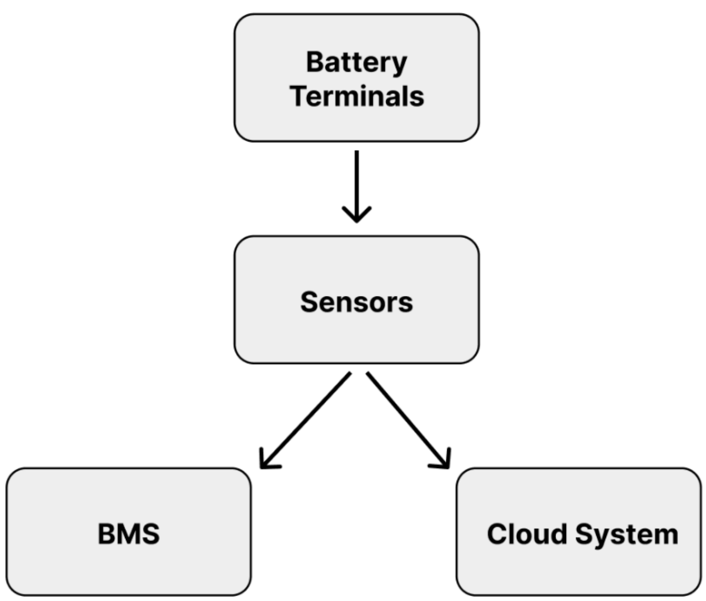


Fig: 21: Block diagram of the diagnostic sensor subsystem

Table 24 lists components within the diagnostic sensor subsystem, explaining their inputs, outputs, and roles in measuring battery health indicators.

TABLE 22: DIAGNOSTIC SENSOR SUBSYSTEM COMPONENTS

Component	Inputs	Outputs	Functionality
Voltage sensors	Battery terminals	Voltage data	Measures voltage for real-time analysis
Current sensors	Current flow	Current data	Monitors current to detect irregularities
Temperature sensors	Ambient/battery Surface	Temp data	Tracks thermal conditions to prevent overheating

Fig. 23 illustrates the cloud system, showing data flow from the BMS and sensors to the cloud for storage and analysis. This enables predictive analytics and remote access to historical battery data.

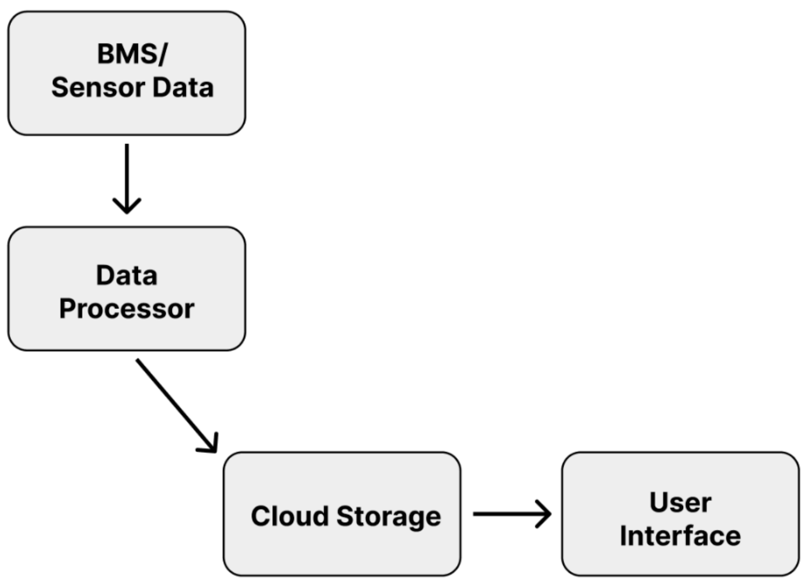


Fig. 23: Block diagram of the cloud subsystem

Table 23 lists the cloud system components' input, output, and role in data processing and storage.

TABLE 24: CLOUD SUBSYSTEM COMPONENTS

Component	Inputs	Outputs	Functionality
Data processor	Sensors/BMS Data	Analyzed insights	Processes raw data for predictive analysis
Cloud storage	Data streams	Stored records	Maintains data for trend analysis and reporting

Fig. 24 details the user interface, demonstrating how it displays real-time battery status and receives user commands to customize the tool's operations.

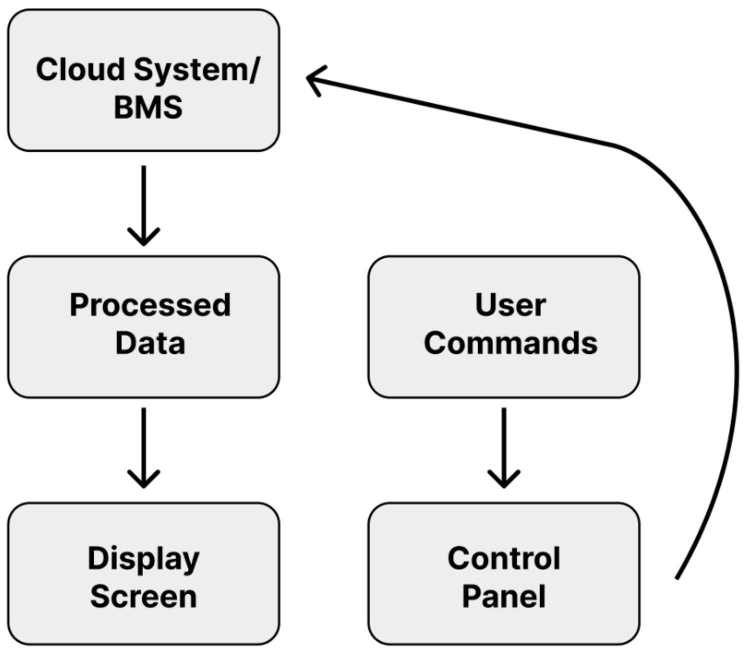


Fig. 24: Block diagram of the user interface subsystem

Table 26 describes the components of the user interface and their roles in ensuring effective interaction between the user and the tool.

TABLE 25: USER INTERFACE COMPONENTS

Component	Inputs	Outputs	Functionality
Display screen	Processed data	Visual output	Shows real-time data and analytical results
Control panel	User input	Command signals	Enables users to adjust settings and interact

A. *Specifications*

The specifications section outlines the technical requirements of the battery prognostic tool, ensuring it adheres to industry standards for accurate and reliable performance. This section includes hardware and input/output specifications, offering a clear overview of the tool's capabilities.

Table 27 provides the hardware specifications, detailing key components such as the microcontroller, sensors, storage, display, and power supply, ensuring a comprehensive understanding of the tool’s design and functionality.

TABLE 26: HARDWARE SPECIFICATIONS

Specification	Details
Microcontroller	Raspberry Pi Pico (SC0917) or STM32F746G-DISCO
Battery Management System	Orion BMS 2

D. *Other Deliverables*

In addition to the Prognostic Tool, we will provide several key deliverables to ensure comprehensive support and documentation for users. This Section outlines these deliverables, which are essential for supporting the product's use and maintenance.

This table lists the additional deliverables for the project, describing their purpose and content. It includes the User and Technical Documentation, Firmware Updates, Final Report, and Final Canva Presentation, ensuring that all necessary documentation and support materials are provided to users and stakeholders.

TABLE 27: PROJECT DELIVERABLES

Deliverable	Description
User Documentation	Basic User Manual
Technical Documentation	Documentation of how the product works
Firmware Updates	Updates via GitHub
Final Report	A final approved report
PowerPoint Presentation	Final Presentation highlighting the functionality of the project

The End Product Description and Other Deliverables section provides detailed tool specifications by clearly describing the product's features and additional deliverables. This is essential to give the customer a clear picture of what to expect when they use the tool. The product meets the needs of industry and individual needs, as it provides advanced analysis on SOC AND SOH processing in a user-friendly, affordable, and accessible format. The final product description explains why the prognostic tool is the best choice for customers requiring a thorough electric battery management system analysis. In addition, regular updates and detailed documentation on the product add to its value. This ensures that a growing repository of information and interactions is available.

XIX. Plan of Action

This action plan outlines our team's structured approach to developing a comprehensive Li-Ion Battery Prognostic and Diagnostic Tool. We aim to ensure a clear and organized development process by dividing the project into well-defined phases, each with specific objectives, tasks, and deliverables. From initial concept design and machine learning model selection to system deployment and performance evaluation, each stage will be guided by a detailed Statement of Work (SOW), establishing the project scope, roles, and responsibilities. A Work Breakdown Structure (WBS) will break the project into manageable tasks. Gantt and PERT charts will be utilized to visualize timelines, monitor progress, and manage task dependencies, ensuring smooth project execution and timely completion.

A. ***Statement of Work***

The Statement of Work outlines the tasks, responsibilities, deliverables, and timeline for developing the Li-Ion Battery Prognostic and Diagnostic Tool. The goal is to create a versatile, hybrid cloud/edge-based system that utilizes machine learning and real-time diagnostics to predict battery State-of-Health (SOH) and State-of-Charge (SOC) and extend battery lifespan through advanced monitoring.

1) Scope of Work

Our team is developing a robust real-time diagnostic tool to monitor battery health, incorporating hardware and software components. The hardware involves a Raspberry Pi connected to a Battery Management System (BMS) for data acquisition and edge processing. On the software side, the system will employ ML models for anomaly detection, health prediction, and reinforcement learning (RL) for adaptive diagnostics. The project will include a user-friendly web interface for remote monitoring and cloud integration for centralized data storage and advanced ML processing.

2) Hardware Tasks

The initial setup will utilize a Raspberry Pi to collect data from the BMS and ensure reliable signal capture for diagnostic accuracy. The hardware design will incorporate sensors and interfaces for data transmission to the cloud. Prototyping will be done on a Raspberry Pi as a microcontroller with all the necessary components to establish stable data acquisition. Edge ML models will be optimized to run on the Raspberry Pi and the cloud, with data processing carried out locally and online. The data will be uploaded to cloud storage when connected.

3) Software Tasks

On the software side, Python libraries such as Scikit-learn, TensorFlow, and PyTorch will be used to implement ML models for battery health predictions. Flask or Django will be employed to develop an intuitive web-based interface, allowing users to monitor SOC and SOH remotely. Key software features include K-Means clustering for anomaly detection, neural networks for SOH and SOC prediction, and reinforcement learning algorithms for adaptive diagnostics. The software will also support offline diagnostics on the Raspberry Pi, syncing data to the cloud when connectivity is available.

4) Location of Work

As in-person students working closely on campus, we will conduct our project collaboration primarily through in-person meetings and online tools. Our main collaboration tools include:

- **Microsoft Teams**: For virtual meetings, file sharing, and coordinated discussions with our mentor and any remote team members.
- **WhatsApp**: For quick updates and informal group discussions.
- **SharePoint**: To store and collaborate on shared documents, ensuring everyone can access the latest project files and resources.
- **GitHub**: Used for version control of code, firmware, and project documentation, making it easy for all team members to access and contribute.

This setup allows for efficient communication, organized documentation, and seamless collaboration both in person and online.

5) Period of Performance

Our project timeline spans from September 2024 to April 2025 and is organized into distinct phases to ensure steady progress and thorough development. The timeline is as follows:

- **September 2024**: Research Phase – We began with in-depth research on battery management systems (BMS), machine learning algorithms for State of Charge (SOC) and State of Health (SOH) prediction, and the potential of cloud integration.
- **Mid-October 2024**: Prototyping Phase – Initial prototyping commenced, focusing on learning the Machine Learning Algorithms and the technology for interface prototyping.
- **Mid-November 2024**: Data Collection – Gathering actual or simulated data from the BMS to test our algorithms in local and cloud environments.
- **Early December 2024**: Draft Development – Complete a rough draft of the diagnostic tool, including a web interface prototype and basic ML model functionality.
- **January - April 2025**: Refinement and Finalization – We will optimize the ML algorithms, enhance the user interface, conduct hardware-in-the-loop testing, and prepare the final delivery of the Battery Prognostic and Diagnostic Tool.

This structured approach ensures a systematic progression from research to prototype and final deployment, meeting key project milestones within each phase.

6) Deliverables Schedule

- To ensure the timely and successful completion of the Battery Prognostic and Diagnostic Tool project, we have established a clear schedule of deliverables. Each phase includes specific milestones to guide our progress. Below is the comprehensive list of deliverables, along with their due dates:

September 2024: Research Phase

- Project Scope
- Market Research on BMS and ML Algorithms
- Initial Selection of Cloud and Local Development Tools
- Role Assignment

Mid-October 2024: Prototyping Phase

- Initial Data Collection and Processing Code (Software)
- Initial Testing of Data Transfer to Cloud
- Plan for Prototype Iteration Based on Initial Feedback

Mid-November 2024: Data Collection Phase

- Integration of ML Algorithms for SOC and SOH Prediction
- First Round of Data Collection (Real/Simulated)
- Prototype Web Interface for Battery Health Monitoring
- Initial Testing of Data Syncing to Cloud (AWS/Azure)

Early December 2024: Draft Development Phase

- Rough Draft of the Battery Prognostic and Diagnostic Tool
- Preliminary ML Model for Battery Health Prediction (SOC/SOH)
- Web Interface Prototyping Completed
- Initial Documentation for Development Process

January - April 2025: Refinement and Finalization

- Optimization of ML Algorithms for Accuracy and Speed
- Enhancement of User Interface for Real-Time Monitoring
- Hardware-in-the-Loop Testing for Real-World Simulation
- Full Cloud Integration and Final Data Synchronization Testing
- Final Project Documentation
- Beta Testing
- Final Presentation and Delivery
- This deliverable schedule ensures the project progresses systematically through research, prototyping, data collection, refinement, and final delivery while meeting critical deadlines.

7) Responsibilities

To ensure the successful design and development of the Battery Prognostic and Diagnostic Tool, each team member has been assigned specific tasks based on their skill sets and preferences. This approach ensures that every member can contribute effectively while gaining experience across all aspects of the project. Below are the roles and responsibilities of each team member throughout the project:

a) Franko Sanabria – Team Lead/Project Lead

As the project lead, Franko will oversee project execution, manage timelines, and ensure all phases stay on track. In addition to his project management responsibilities, he will contribute directly to AI model development and interface design, coordinating with both the AI and Interface leads. Franko will also handle task assignments and facilitate team meetings, ensuring smooth communication and documentation.

b) Sebastian Munoz – Cloud Lead

Sebastian will implement and manage the cloud infrastructure for real-time data transmission and storage. He will oversee data synchronization between the Raspberry Pi and the cloud, ensuring security, reliability, and scalability. Additionally, he will integrate the cloud resources with the web interface and support real-time monitoring for SOC and SOH predictions.

c) Roberto Valdes – Interface Development Lead

Roberto will design and develop the user interface for monitoring battery health and diagnostics. He will ensure the interface is intuitive, visually appealing, and accessible on multiple devices. Roberto will work closely with Franko and Joshua to incorporate real-time data visualization and facilitate easy access to the battery's SOC and SOH predictions.

d) Joshua Natal – AI Lead

Joshua will lead the development of the machine learning models for SOC and SOH prediction. His tasks include selecting suitable ML algorithms, training models on the data collected from the BMS, and fine-tuning the models for accuracy. Depending on computational requirements, he will also coordinate with Franko to integrate the models on the Raspberry Pi or in the cloud.

e) Jacob Stafford – Testing and Hardware/Data Collection Lead

Jacob will focus on testing and verifying the hardware components and data collection processes. He will design protocols for testing the Raspberry Pi's connection to the BMS and validate the accuracy of data transmission to the cloud. Additionally, he will manage data collection for model training and oversee hardware-in-the-loop testing to ensure real-world reliability.

By defining these roles clearly, we can optimize team efficiency while providing each member with opportunities to engage with all aspects of the project. This collaborative approach supports a comprehensive development process, producing a high-quality final deliverable.

8) Work Breakdown Structure

The Work Breakdown Structure (WBS) is an essential framework for organizing the Battery Prognostic and Diagnostic Tool project into smaller, manageable tasks. This structured approach helps the team focus on each specific phase, from research and development to final testing and deployment. By decomposing larger objectives into detailed, actionable items, the WBS ensures that all efforts align toward achieving the project's goals. It also provides a clear visual representation of the project's scope, tasks, and dependencies, facilitating better planning, task assignment, and execution. Figure 25 illustrates our team's WBS, showing the interrelated tasks and phases required to deliver a high-quality, functional diagnostic tool for battery health monitoring.

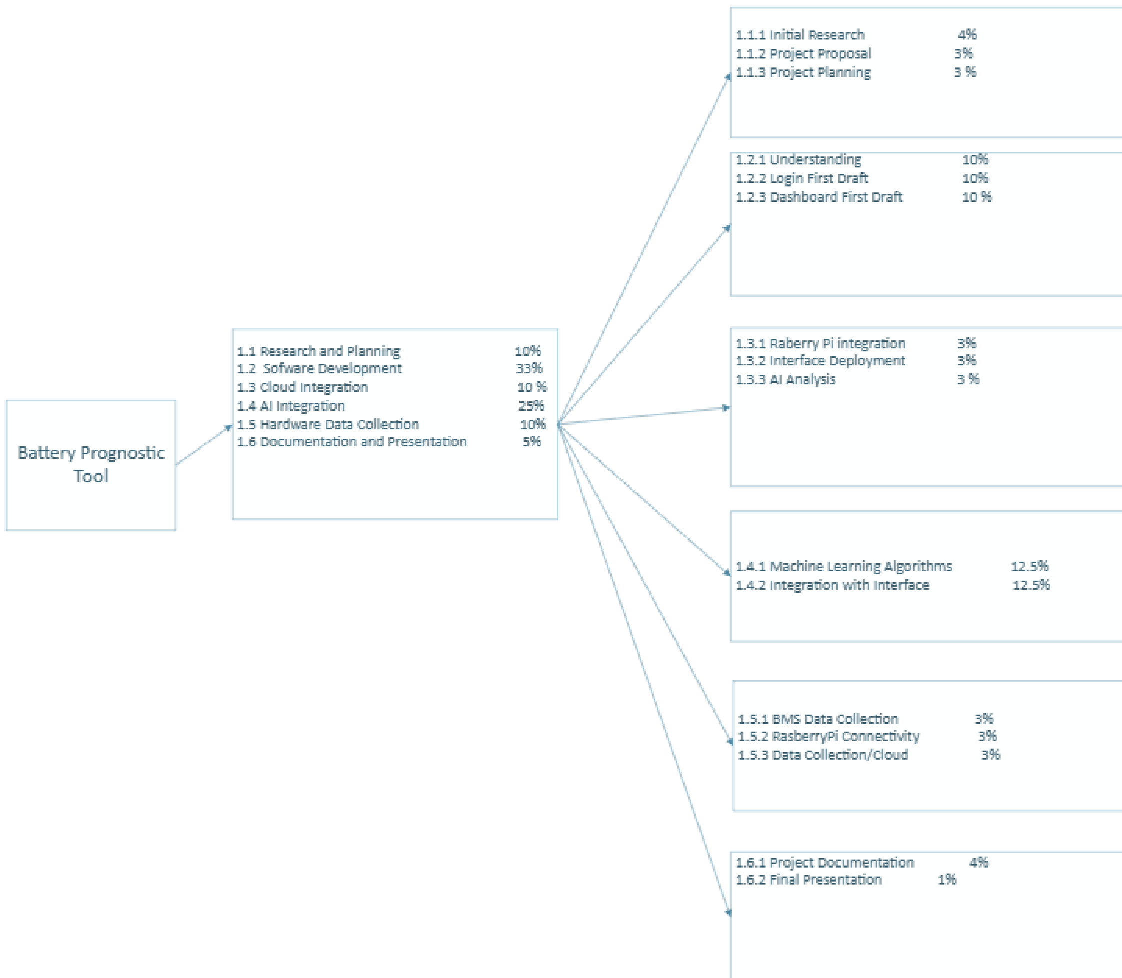


Fig. 25: Work breakdown structure diagram

9) *Research and Planning*

Objective: Define the Battery Prognostic and Diagnostic Tool project's primary goals, technical requirements, and constraints. Assess various cloud and edge processing options, establish the team's work environment, and formulate a comprehensive project plan.

Approach: Conduct stakeholder interviews and surveys to capture critical objectives and constraints. Investigate and evaluate local vs. cloud-based machine learning processing options, considering latency, cost, and scalability factors. Establish a shared development environment on Microsoft Teams and assign specific roles based on each member's expertise.

Expected Results: Obtain a well-defined understanding of project requirements and technical constraints, facilitating efficient task management and collaboration across the team.

Actual Results: Stakeholder interviews clarified core project goals and constraints, including the need for real-time diagnostics and predictive capabilities. Setting up the development environment on Microsoft Teams enhanced communication and streamlined file sharing, creating a productive workflow for the team.

10) Hardware Design

Objective: Design and integrate the hardware setup to collect and transmit battery data from the BMS. Establish seamless data flow from the Raspberry Pi to the cloud, ensuring accurate data capture for real-time diagnostics and predictive analysis.

Approach: Develop and prototype the sensor interfacing and data collection setup using a Raspberry Pi connected to the BMS. Please verify the accuracy of collected signals by measuring them with appropriate tools, such as an oscilloscope, and configure necessary encoders and input/output interfaces. Once validated, order and assemble PCBs tailored for the finalized hardware design and ensure compatibility with cloud transmission protocols.

Expected Results: A reliable hardware setup that consistently captures accurate BMS data, prepared for cloud integration and data-driven analysis.

11) Software Development

Objective: Develop software to collect and process battery health and performance data, create an intuitive user interface, and implement additional diagnostic features.

Approach: Program the microcontroller to collect data from battery sensors, focusing on analyzing battery charge, discharge rates, temperature, and voltage variations. Design an intuitive user interface that displays health metrics in real-time.

Expected Results: A functional software suite that supports real-time data monitoring with a straightforward, user-friendly interface and enhanced diagnostic features, enabling users to assess battery health efficiently.

12) AI Development

Objective: Develop AI algorithms to predict battery failure and performance degradation, ensuring all hardware and software components meet accuracy and reliability standards.

Approach: Design and test machine learning models to detect patterns in battery health data and predict potential issues before they occur. Use collected data to refine the algorithms and improve accuracy. Conduct rigorous testing and debugging to ensure that predictions are timely and reliable. Gather feedback from test users to enhance model usability and relevance.

Expected Results: A robust AI component capable of accurately predicting battery health issues with minimal error rates, integrated seamlessly into the data collection system

13) Documentation and Presentation

Objective: Compile all project documentation and prepare a final presentation for stakeholders.

Approach: Document system architecture, AI model performance, testing procedures, and user manuals. Prepare detailed reports and presentation slides highlighting critical design decisions, project challenges, and solutions.

Expected Results: A comprehensive set of documents that clearly explains project development stages, provides user guidance, and showcases the tool's effectiveness, accompanied by a polished presentation for stakeholders.

14) Project Milestones

Project milestones serve as benchmarks for tracking the progress of our battery prognostic tool. Achieving these milestones ensures we stay on track, while delays indicate a need to accelerate efforts. Key milestones include:

Completion of Initial Prototype
Develop an initial prototype using Raspberry Pi to handle data collection and processing.

Data Collection Setup
Establish data collection protocols and collect initial battery health metrics.

Cloud Integration
Integrate cloud storage for data logging, allowing easy access to battery performance data.

AI Algorithm Development
Create and test machine learning models to predict battery health trends and potential failures.

User Interface Implementation
Design and integrate a user-friendly interface on the Raspberry Pi to display health metrics and predictions.

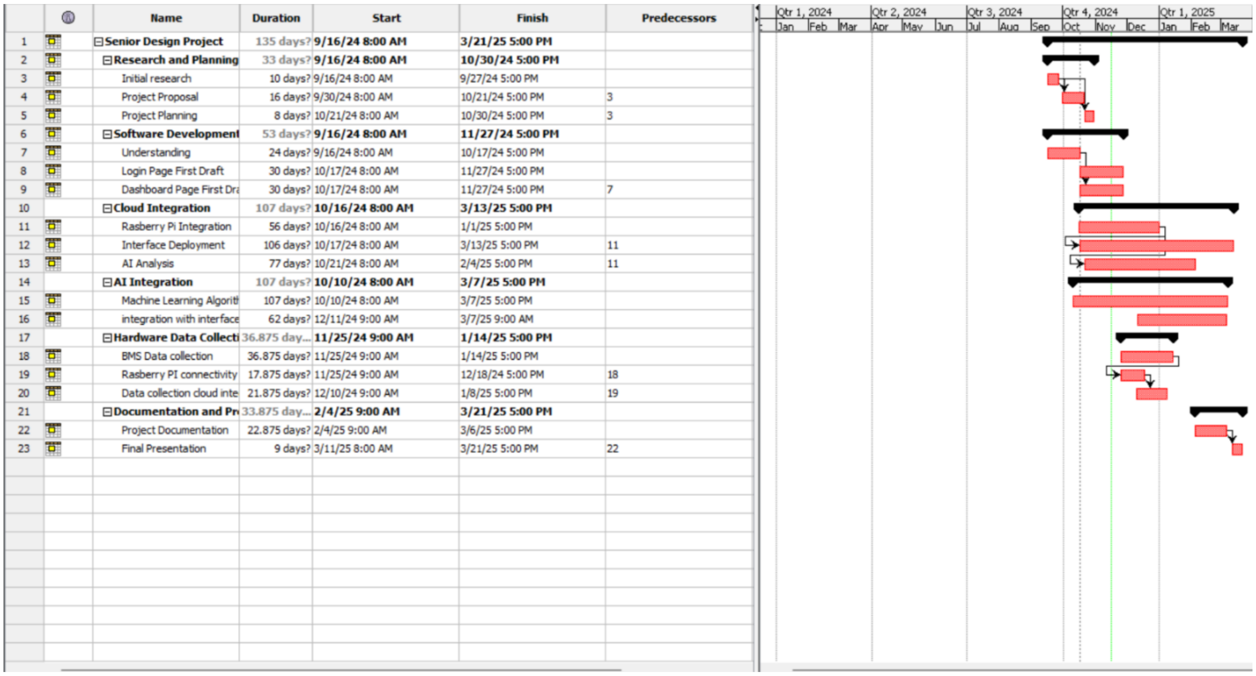
Comprehensive Testing and Debugging
Conduct thorough testing and debugging to ensure the accuracy and performance of all components.

Final Presentation and Documentation
Compile all documentation and prepare a presentation showcasing the tool’s capabilities and accuracy.

By adhering to these milestones, our team ensures the project’s success and timely completion.

15) Gantt Chart

Gantt charts are critical visual tools in project management, used to plan, schedule, and track tasks over a set time frame. These charts represent the project's timeline, emphasizing the duration and dependencies of each task. Gantt charts help ensure the project moves forward logically and efficiently by indicating which tasks must be completed before others begin. They are invaluable in monitoring our team's plan execution and making necessary schedule adjustments. Figure 26 depicts our planned tasks and their durations.



	Name	Duration	Start	Finish	Predecessors
1	**Senior Design Project**	135 days?	**9/16/24 8:00 AM**	**3/21/25 5:00 PM**	
2	**Research and Planning**	33 days?	**9/16/24 8:00 AM**	**10/30/24 5:00 PM**	
3	Initial research	10 days?	9/16/24 8:00 AM	9/27/24 5:00 PM	
4	Project Proposal	16 days?	9/30/24 8:00 AM	10/21/24 5:00 PM	3
5	Project Planning	8 days?	10/21/24 8:00 AM	10/30/24 5:00 PM	3
6	**Software Development**	53 days?	**9/16/24 8:00 AM**	**11/27/24 5:00 PM**	
7	Understanding	24 days?	9/16/24 8:00 AM	10/17/24 5:00 PM	
8	Login Page First Draft	30 days?	10/17/24 8:00 AM	11/27/24 5:00 PM	
9	Dashboard Page First Dra	30 days?	10/17/24 8:00 AM	11/27/24 5:00 PM	7
10	**Cloud Integration**	107 days?	**10/16/24 8:00 AM**	**3/13/25 5:00 PM**	
11	Rasberry Pi Integration	56 days?	10/16/24 8:00 AM	1/1/25 5:00 PM	
12	Interface Deployment	106 days?	10/17/24 8:00 AM	3/13/25 5:00 PM	11
13	AI Analysis	77 days?	10/21/24 8:00 AM	2/4/25 5:00 PM	11
14	**AI Integration**	107 days?	**10/10/24 8:00 AM**	**3/7/25 5:00 PM**	
15	Machine Learning Algorit	107 days?	10/10/24 8:00 AM	3/7/25 5:00 PM	
16	integration with interface	62 days?	12/11/24 9:00 AM	3/7/25 9:00 AM	
17	**Hardware Data Collecti**	36.875 day...	**11/25/24 9:00 AM**	**1/14/25 5:00 PM**	
18	BMS Data collection	36.875 days?	11/25/24 9:00 AM	1/14/25 5:00 PM	
19	Rasberry PI connectivity	17.875 days?	11/25/24 9:00 AM	12/18/24 5:00 PM	18
20	Data collection cloud inte	21.875 days?	12/10/24 9:00 AM	1/8/25 5:00 PM	19
21	**Documentation and Pr**	33.875 day...	**2/4/25 9:00 AM**	**3/21/25 5:00 PM**	
22	Project Documentation	22.875 days?	2/4/25 9:00 AM	3/6/25 5:00 PM	
23	Final Presentation	9 days?	3/11/25 8:00 AM	3/21/25 5:00 PM	22

Fig. 26: Gantt chart with schedule and assignments

PERT Chart

The Program Evaluation Review Technique (PERT) chart is a valuable project management tool that supplements the Gantt chart by emphasizing the interdependence of different tasks or phases. It shows project tasks in order of priority, allowing us to identify the critical path—the most extended sequence of dependent tasks required for project completion. This helps prioritize efforts and ensures all tasks are completed on time. Figure 27 shows our team's PERT chart, highlighting our project's dependencies and critical paths.

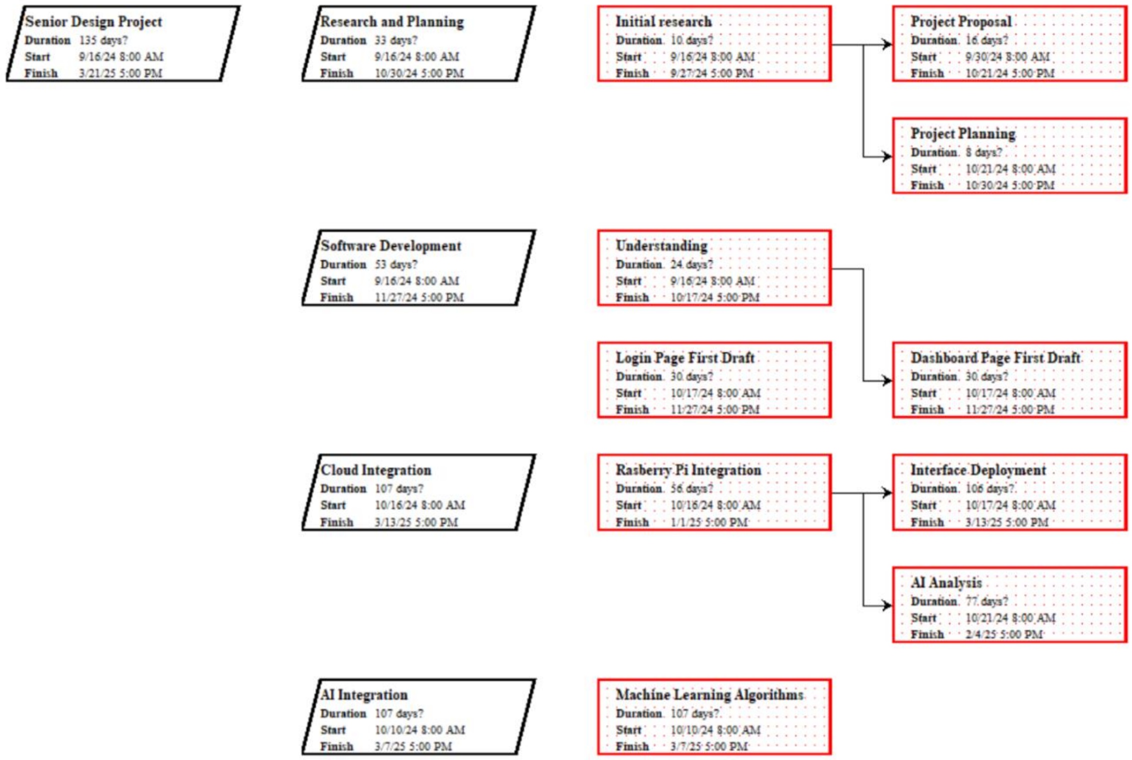


Fig. 27: PERT chart for multi-effects guitar pedal project

XX. MULTIDISCIPLINARY ASPECTS

A team with various technical skills is needed to develop a dependable and efficient battery prognostic and diagnostic tool. Our diverse team of electrical and computer experts brings together complementary expertise in cloud computing, machine learning, data management, interface design, and project leadership. With the common objective of creating an innovative and effective diagnostic tool, we take advantage of each team member's unique strengths to approach the project from several angles, strengthening our ability to handle its logistical and technical aspects.

Our team is composed of five members with specialized roles, allowing us to tackle different aspects of the project collaboratively:

- **Sebastian Munoz - Cloud Integration and Raspberry Pi**
    - **Background**: Electrical Engineer
    - **Skills and Expertise**: Experienced in cloud computing, data processing, and IoT integration
    - **Contribution**: Manages the cloud infrastructure and works with the Raspberry Pi to ensure data storage and accessibility for real-time diagnostics.
- **Joshua Natal - Machine Learning and Computing**
    - **Background**: Electrical Engineer
    - **Skills and Expertise**: Proficient in machine learning, data analytics, and computing algorithms
    - **Contribution**: Develops predictive models and machine learning algorithms for battery health analysis, enhancing the tool's prognostic capabilities.
- **Jacob Stafford - Data Gathering and Raspberry Pi Implementation**
    - **Background**: Electrical Engineer
    - **Skills and Expertise**: Skilled in sensor integration, data collection, and hardware-software interfacing
    - **Contribution**: Gather essential diagnostic data through the Raspberry Pi, ensuring accurate and reliable input for analysis.
- **Roberto Valdes - Interface Development**
    - **Background**: Computer Engineer
    - **Skills and Expertise**: Experienced in user interface design, software development, and system integration
    - **Contribution**: Focuses on creating a user-friendly interface, allowing end-users to access and interact with diagnostic data effectively.
- **Franko Sanabria- Project Management and Interface Support**

Background: Electrical Engineer

Skills and Expertise: Skilled in project coordination, task scheduling, and some interface development

Contribution: Leads the team as Project Manager, coordinating tasks and managing timelines while assisting with interface design and AI development as needed.

Leadership and Management Plan:

To maintain project momentum over the semester break, we have a management strategy that includes the following:

- **Leadership Structure**: Franko, as Project Manager, will organize team efforts, track progress, and facilitate bi-weekly meetings to ensure consistent focus on project objectives.
- **Activity Management During Breaks**:
- **Task Assignment**: Specific tasks with deadlines will be assigned to each team member before the break to keep everyone productive.
- **Remote Collaboration**: Tools like Teams and Github will support communication and progress tracking during the break period.
- **Progress Check-Ins**: Franko will conduct regular check-ins with each member to monitor progress and address any issues promptly.
- **Preparation for Next Semester**: We'll develop a clear project roadmap to ensure the team can resume work efficiently when the new semester begins.

Our team's combination of cloud, machine learning, data gathering, interface, and project management skills allows us to comprehensively address every aspect of the battery prognostic and diagnostic tool. With a balanced approach to leadership and collaboration, we are well-prepared to deliver a functional and effective tool, maintaining productivity even through semester transitions.

XXI. PERSONNEL

Our team comprises a unique combination of engineers with complementary computer and electrical engineering talents. The skills of each team member improve our approach to hardware, software, data analytics, and project management, which helps us successfully create our battery prognostic and diagnostic tool. A thorough summary of each member's training, work history, and abilities can be found below.

*A. **Joshua Natal***

- **Education**: Bachelor of Science in Electrical Engineering (Expected May 2025); GPA: 3.87
- **Relevant Coursework**: Power Systems, Electronics, Circuit Analysis, Logic Design, Differential Equations
- **Work Experience**:
  - **Northrop Grumman – Electrical Engineering Intern**
    Supported Power Conversion Technology (PCT) team projects by contributing to over 30 automated tests and reviewing critical circuit card assembly (CCA) revisions. Gained extensive experience in analyzing electrical schematics and PCB designs using tools like Xpedition Designer and LTSpice, ensuring design specifications within a 1% tolerance. Acquired deep knowledge of power converter topologies and electromagnetic compatibility.
  - **FIU College of Engineering – Undergraduate Research Assistant**
    Advanced the Department of Energy's RENEW project, integrating semiconductor physics with VLSI design concepts. Delivered 12+ technical presentations, achieving 100% confirmation of project feasibility through in-depth analysis.
- **Technical Skills**: C++, Java, SolidWorks (CSWA), AutoCAD, proficiency in embedded systems, and Spanish (semi-fluent).
- **Contributions**: Joshua is responsible for designing and implementing critical diagnostic circuits for the tool. His extensive experience in power electronics, embedded systems, and technical analysis supports the project's hardware and circuit development.

*B. **Roberto Valdes***

- **Education**: Bachelor of Science in Computer Engineering (Expected May 2025); GPA: 3.79
- **Relevant Coursework**: Embedded Systems Programming (C, C++), Data Structures, Machine Learning, CAD Design
- **Work Experience**:
  - **Miami Heat – E-commerce & Technology Services Intern**
    We developed a chatbot using Python and GPT models for real-time customer interactions and automated inventory management. Responsible for ensuring accurate stock levels for over 200 items, contributing to efficient operations.
  - **Mango (Startup) – Full-Stack Developer and Co-founder**
    Designed a user-friendly interface and backend system for a farm-to-restaurant ordering platform. Integrated Stripe and SendGrid APIs to streamline inventory management, reducing food waste by 15%.

- **Technical Skills**: Python, Java, React, Azure Fundamentals, Spark, 3D printing, and machine learning.
- **Contributions**: Roberto leads the machine learning component of the project, utilizing his knowledge in predictive modeling and data analysis to enhance the tool's ability to forecast battery performance. His experience with full-stack development ensures seamless software integration.

*C. **Jacob Stafford***

- **Education**: Bachelor of Science in Electrical Engineering,
  (Expected May 2025)
- **Relevant Coursework**: Advanced Circuit Design, Control Systems, Electrical Machinery, Embedded Systems
- **Work Experience**:
  - **United States Navy – Avionics Technician**
    Performed scheduled and unscheduled maintenance on aircraft electronics, managing a team of 32 technicians. Oversaw quality assurance inspections and preventive maintenance tasks, achieving a 38% reduction in backlog maintenance. Conducted complex troubleshooting for avionic and electrical systems using oscilloscopes, multimeters, and specialized test benches.
  - **Benteler Automotive – Gage Technician**
    Responsible for accurately measuring chassis components and robotic arm maintenance, improving the efficiency of automotive parts manufacturing.
- **Technical Skills**: Circuit wiring, navigation systems, electrical repair, schematics analysis, and critical safety compliance.
- **Contributions**: Jacob specializes in hardware testing and diagnostics for the project. His military background in avionics brings a high level of discipline and precision to quality assurance, ensuring the reliability of each component.

*D. **Franko Sanabria***

- **Education**: Bachelor of Science in Electrical Engineering
  (Expected May 2025); GPA: 3.68
- **Relevant Coursework**: Embedded Systems Programming, Data Structures, Algorithms, Machine Learning Applications
- **Work Experience**:
  - **Microsoft – Software Engineer Intern**
    Developed real-time anomaly detection models using .NET and PowerShell for telemetry data analysis. Led the implementation of custom sensors following the MITRE ATT&CK framework and enhanced system security by integrating language model-powered PowerShell scripts.
  - **Microsoft Explore Intern**
    Created a quantum-based secure private key generator, incorporating post-quantum lattice-based algorithms for cybersecurity applications. Integrated the solution using Flask APIs and containerized the application for seamless deployment.
- **Technical Skills**: C, C++, Python, Java, Docker, Flask, and CNC machine operation.

- **Contributions**: Franko supports both the software development and project coordination aspects. His experience with machine learning and software engineering is invaluable to the project's predictive functions and anomaly detection capabilities.

*E. **Sebastian Munoz***

- **Education**: Bachelor of Science in Electrical Engineering
  (Expected May 2025); GPA: 3.7
- **Relevant Coursework**: Circuit Design, Embedded Systems, Programming for Engineers, Power Electronics
- **Work Experience**:
  - **Lexus of Kendall – Automotive Technician**
    Gained hands-on experience in automotive diagnostics and troubleshooting various electronic and mechanical issues. Worked with advanced diagnostic tools, ensuring compliance with safety standards and delivering high-quality repair solutions.
  - **J&B Imports – Warehouse Sorter**
    Responsible for efficient material handling and inventory management, operating heavy equipment safely to optimize stock flow.
- **Technical Skills**: AutoCAD, Microsoft Office Suite, Circuit Analysis. Bilingual in English and Spanish.
- **Contributions**: Sebastian is responsible for cloud data integration and user interface development. His team coordination and user-centered design proficiency ensure effective communication across the project's software and hardware elements.

Our multidisciplinary team's combined computer and electrical engineering knowledge enables us to approach the project comprehensively. The backgrounds of each team member help to create an innovative battery prognostic and diagnostic tool that offers accurate diagnostics and efficient project execution.

XXII. BUDGET

Budgeting is crucial in developing every project, and that doesn't change for our Battery Management System. Setting a budget establishes realistic goals while ensuring project objectives are achieved within financial constraints and on time. Careful budgeting allows us to make financial decisions efficiently and prioritize spending on the more essential project components while ignoring less critical parts. Table 1 provides an overview of the projected costs by design phase.

TABLE 28: PROJECTED PROJECT COSTS BY DESIGN PHASE.

Project Phase	**Cost**
Hardware Design	$3,500.00
Circuit Design	$750.00
Software Development	$5,500.00
System Integration	$1,500.00
Interface Development	$1,000.00
Testing and Validation	$800.00
Yearly cloud service	$600.00
Total Project Cost	$13,650.00

A. *Labor Costs*

Table 2 outlines the anticipated labor costs for our project by team member. We have based the labor rate at $46 per hour, reflecting the average starting salary for an electrical engineer in the Miami metropolitan area (13). This calculation excludes additional employment-related costs such as insurance, retirement, and health benefits.

TABLE 29: LABOR COST BREAKDOWN BY TEAM MEMBER.

Team Member	Hours Worked	Cost Per Unit	Total
Franko Sanabria	100	$46	$4,600.00
Joshua Natal	80	$46	$3680.00
Roberto Valdes	80	$46	$3680.00
Jacob Stafford	80	$46	$3680.00
Sebastian Munoz	80	$46	$3680.00
Total Labor			$19,320.00

B. ***Hardware Components***

Table 3 shows the expected physical hardware component costs for constructing the BMS prototype. Initial expenses are anticipated to be higher as components are purchased in low volumes, and development kits may be used during prototyping.

TABLE 30: HARDWARE COMPONENT COSTS

Component	Quantity	Cost Per Unit	Total
Battery Sensors	1	$400.00	$400.00
Power Management ICs	1	$100.00	$100.00
Microcontroller	1	$100.00	$100.00
Enclosure	1	$150.00	$150.00
Circuit Board	1	$200.00	$200.00
Total Components			***$950.00***

C. ***Total Project Cost***

When you add the projected project design cost and the salary we would make for this project, the total price goes up to around $34,000.00. This budget is a fundamental part of our project management, as it reflects the financial resources needed to complete specific tasks and ensure the successful execution of the project. This budget considers the development, the personnel, and the physical device itself, making it a complete budget.

XXIII. Results Evaluation

This section outlines the methods and criteria to evaluate the Battery Prognostic and Diagnostic Tool results. The evaluation will ensure that our objectives and constraints are met, adhering to necessary standards and specifications. Defining these metrics establishes clear goals and benchmarks for assessing progress.

A. *Objectives*

Table 34 presents our team's objectives while developing the Battery Prognostic and Diagnostic Tool.

TABLE 31: OBJECTIVES FOR THE BATTERY PROGNOSTIC AND DIAGNOSTIC TOOL

Objective	Description
User-Friendly Interface	Design a web-based application accessible via cloud hosting. The interface will display real-time battery data, predict SOC and SOH, and allow user interaction.
Seamless Cloud Integration	Ensure constant data transfer from the Raspberry Pi to cloud storage platforms like AWS S3 or Azure Blob. Optimize for efficiency in cloud communication.
Machine Learning Accuracy	Implement and validate ML algorithms (e.g., K-Means and neural networks) for SOC and SOH predictions, targeting high accuracy and reliability.
Hardware Compatibility	Develop compatibility with the Battery Management System (BMS) to collect real-time data and run ML models locally or in the cloud.

B. Constraints

Table 35 details the constraints that will guide the design and implementation of the tool.

TABLE 32: Constraints on the design of the Battery Prognostic and Diagnostic Tool

Constraint	Description
Hardware Limitations	Raspberry Pi must efficiently process data and run lightweight ML models without exceeding memory or compute limits.
Offline Functionality	When cloud access is unavailable, the tool must provide limited offline capability for local data processing and ML inference.
Cost Efficiency	Prioritize cost-effective components and cloud services to minimize development and operational expenses.
Latency Requirements	Ensure real-time or near-real-time updates for data display and ML predictions to meet user expectations.

C. Standards to Comply With

The Battery Prognostic and Diagnostic Tool will adhere to several standards to ensure safety, performance, and regulatory compliance:

1. **IEEE 1725**: Standards for rechargeable batteries, ensuring the safety and reliability of the integrated BMS.
2. **IEC 61508**: Functional safety standards for systems employing electronic hardware to ensure robustness and fault tolerance.
3. **ISO 15118**: Standards for electric vehicle interoperability, where applicable, to integrate with vehicle battery management systems.
4. **Data Privacy Regulations**: Ensure compliance with data handling standards like GDPR or CCPA to protect user data integrity and confidentiality.

D. Patents not to infringe

Comprehensive research will be conducted to identify and avoid patents in battery management, machine learning for SOC/SOH prediction, and cloud integration technologies. To ensure originality, databases such as USPTO and EPO will be used for patent checks.

E. Specifications

The following specifications outline the goals for the Battery Prognostic and Diagnostic Tool:

1. **Power Supply**: Utilize Raspberry Pi's onboard capabilities to power sensors and components. Ensure stable power delivery to all hardware elements.
2. **Machine Learning Models**: Train K-Means and neural networks locally or on the cloud for battery health predictions, aiming for high prediction accuracy and real-time feedback.
3. **Data Transmission**: Implement MQTT or Azure IoT Hub for reliable, low-latency data transfer between the Raspberry Pi and cloud storage.
4. **User Interface**: Develop a responsive web-based Flask or Django application. Provide users with real-time monitoring, historical data visualization, and diagnostic reports.

XXIV. Life-long Learning

Bringing our Battery Management System (BMS) project into production and ensuring its sustainability requires a strategic approach rooted in continuous improvement, market relevance, and professional growth. Lifelong learning is essential to keep up with the rapid pace of technological advancements in battery technology, machine learning, and IoT. Staying current involves immersing ourselves in the latest research, participating in industry conferences, and engaging with professional organizations. With the way AI is used for coding, we will see a rapid advancement in how our code can process data, so regular firmware updates will help us stay in the market.

We would first finalize the prototyping and testing phases to bring the project to production, ensuring compliance with international standards such as IEC 62133 for battery safety and FCC regulations for electronic devices. Collaborating with industry partners and manufacturers would streamline the transition from prototype to mass production. Establishing partnerships with IoT and battery companies would enhance the product's integration into existing markets. Additionally, creating accurate documentation and a user-friendly interface would ensure ease of adoption across various industries.

Our team would need ongoing professional development to keep ourselves current on the relevant topics. This includes attending conferences such as the IEEE Energy Conversion Congress & Exposition and Battery Japan to stay informed about emerging trends. Subscribing to technical journals like IEEE Transactions on Energy Conversion and Journal of Power Sources would provide valuable insights into cutting-edge research. Online courses and certifications in machine learning, IoT, and battery technology on platforms like Coursera and edX would help us deepen our expertise and address new challenges as they arise.

Maintaining market relevance for the BMS requires continuous iteration based on user feedback and investment in research and development. Regular firmware updates are crucial to integrate new features, improve performance, and address potential issues. Partnering with end-users for field testing ensures the system evolves to meet real-world needs. Diversifying BMS applications, such as electric vehicles and renewable energy storage systems, would expand its market potential.

Joining technical societies such as IEEE and SAE International is invaluable for lifelong learning and professional networking. Membership in IEEE offers access to technical resources, research papers, and events that facilitate skill enhancement and industry connections. Engaging in IEEE student activities provides collaboration opportunities with peers and industry experts. Participating in online forums, GitHub projects, and LinkedIn groups focused on energy systems and machine learning fosters collaborative learning and innovation.

In conclusion, sustaining the BMS project and ensuring its success requires a commitment to lifelong learning, market adaptation, and professional engagement. By leveraging technical societies, educational resources, and continuous development, we can keep our project at the forefront of innovation while growing as engineers.

XXV. CONCLUSION

We started the Battery Diagnostic and Prognostic Tool project to address the shortcomings in battery health monitoring. Inspired by the increasing need for effective energy storage in fields such as renewable energy and electric cars, our group recognized a problem in precisely forecasting battery lifespan and performance. To deliver accurate State-of-Health (SOH) estimates and failure forecasts, we developed the concept of combining machine learning and real-time diagnostics through brainstorming sessions within the team and our mentors.

The project's goals underwent notable changes through team discussions, surveys, and interviews with potential users. The significance of offline capabilities and compatibility with existing battery management systems (BMS) was highlighted in earlier interviews. Therefore, we concentrated on creating a hybrid system that could function in local and cloud settings, guaranteeing adaptability for various applications.

This proposal resulted from research and user needs gathering through interviews, survey distribution, and brainstorming design solutions. Through these efforts, we set specific goals, such as developing hardware-in-the-loop (HIL) simulations and putting machine learning methods into practice refined for scenarios with limited resources. Evaluations were carried out to verify compliance with project specifications by comparing simulation results with real-world data.

The tool contributes to society by promoting sustainable energy practices, reducing battery waste through extended lifespans, and enhancing safety by predicting failures before they occur. It aligns with global efforts to improve energy efficiency and reliability, particularly in renewable energy systems and electric vehicles.

Because of this project, the team has a deeper understanding of advanced engineering concepts like real-time diagnostics, machine learning, and system integration. Additionally, it developed fundamental skills in project management, problem-solving, and teamwork, preparing us for lifelong learning and professional growth in engineering disciplines.

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XXVII. Appendices

A. *Team Contract*

1) *Team member's obligations*

As part of the Li-Logic team, each member has specific commitments that ensure the success and integrity of our project, which is focused on predicting the end of life for lithium-ion batteries. The obligations of the team members are outlined as follows:

- **Active participation:** Each member is expected to engage in team discussions and collaborative work sessions actively
- **Task accountability:** Every team member will be assigned specific roles and assignments aligning with their skills, expertise, and interests. Assignments are meant to be dealt with by their respective established deadlines
- **Communication:** Team members must communicate any challenges they encounter and provide frequent updates on their end of the project. Transparency and respect are vital for team cohesion
- **Intellectual property awareness:** Team members must understand and adhere to the guidelines regarding the protection and ownership of intellectual property created during the project, ensuring that all contributions are appropriately documented and attributed

2) *Team member expulsion*

Li-Logic reserves the right to expel a team member if their actions violate the agreed-upon team principles. Expulsion will only be considered under specific circumstances, jeopardizing the team's work, integrity, or cohesion. These circumstances include:

- **Failure to meet obligations:** If a team member consistently fails to complete assigned tasks by the agreed-upon deadlines without providing a valid reason or without prior communication to the team, they may be considered for expulsion. This includes a lack of meaningful contribution or engagement in the project
- **Breach of Confidentiality:** Unauthorized disclosure of proprietary project information, intellectual property, or confidential data, whether intentional or through negligence, will be grounds for immediate expulsion. Team members are required to protect sensitive information as outlined in the project's confidentiality terms
- **Unethical Conduct:** Any conduct that violates ethical research and development practices, such as falsifying data, plagiarism, or any activity that could harm the reputation or legality of the team, will result in immediate consideration for expulsion
- **Lack of Communication and Participation:** If a team member fails to communicate or attend team meetings for an extended period without explaining, the team may review their ongoing participation in the project. Continuous lack of involvement may signal withdrawal of interest and lead to expulsion

B. ***Intellectual Property Contract***

The following Intellectual Property Contract is written solely to fulfill the requirements of the undergraduate class 'Senior Design I & II.' It does not reflect an actual IP agreement between contracted project team members (i.e., undergraduate students). Any project deliverables and subsequent IP developed under this project is considered property of the Energy, Power, Sustainability, and Intelligence (EPSi) group and is bound by the CONFIDENTIALITY AGREEMENT signed on September 13, 2024, between the 'Company' (EPSi), and the contact(s) (Franko Sanabria, Jacob Stafford, Joshua Natal, Roberto Valdes, and Sebastian Munoz).

By providing the initials below, the 'contact(s)' understand and agree to the above statement:

Print Name: Franko Sanabria,

Initials: Initial FS

Print Name: Jacob Stafford,

Initials: Initial JS

Print Name: Joshua Natal,

Initials: Initial JN

Print Name: Roberto Valdes, Initials: Initial RV

Print Name: Sebastian Munoz, Initials: Initial SM

XXVIII. SIGNATURES PAGE

Course Number: EEL 4920 Semester: Fall Year: 2024

Mentor Name: Dr. Arif Sarwat

Senior I Instructor's Name: Dr. Willmer Arellano

Name	PID	E-mail Address	Phone Number
Franko Sanabria	6310783	fsana006@fiu.edu	786-344-2123
Roberto Valdes	6305407	rvald131@fiu.edu	786-587-4031
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Sebastian Munoz	6251919	smuno065@fiu.edu	305-781-0093

	PRINT	SIGNATURE	DATE
Team Leader	Franko Sanabria		
Team Member	Roberto Valdes		
Team Member	Joshua Natal		
Team Member	Jacob Stafford		
Team Member	Sebastian Munoz		
Mentor	Arif Sarwat	DocuSigned by: 567C5BF985A24C7...	12/6/2024