# Creating an IoT setup for Battery Digital Twin

## CP-301: Development Engineering Project


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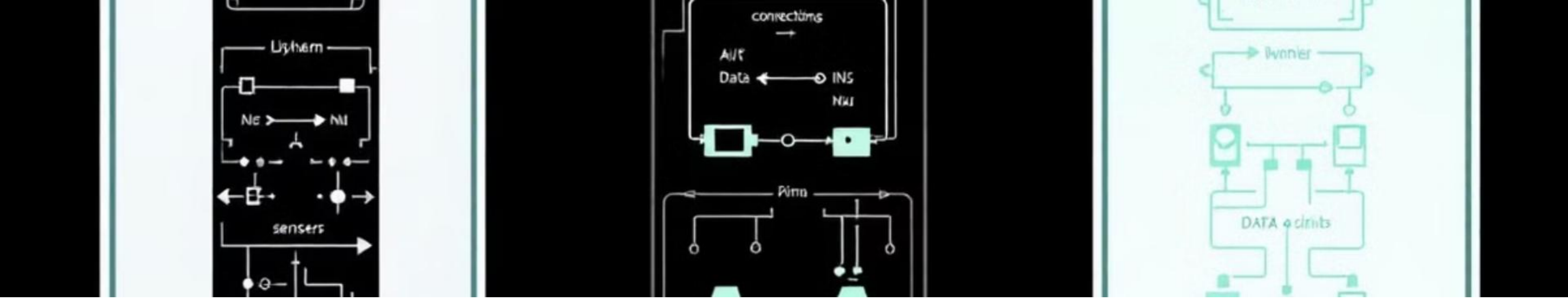
# What Are Digital Twins?

## Concept

Digital twins are virtual models of physical systems that integrate real-time data and analytical models to simulate the behaviour of the physical system in the digital space. They provide a comprehensive understanding of the system's performance and condition.

## Applications

Digital twins have gained traction in various industries, including manufacturing, healthcare, and energy. They enable a wide range of applications, from performance optimization and predictive maintenance to design improvements and risk mitigation.




# Digital Twin Background in Li-ion Battery Systems

1 **Accurate Modelling**

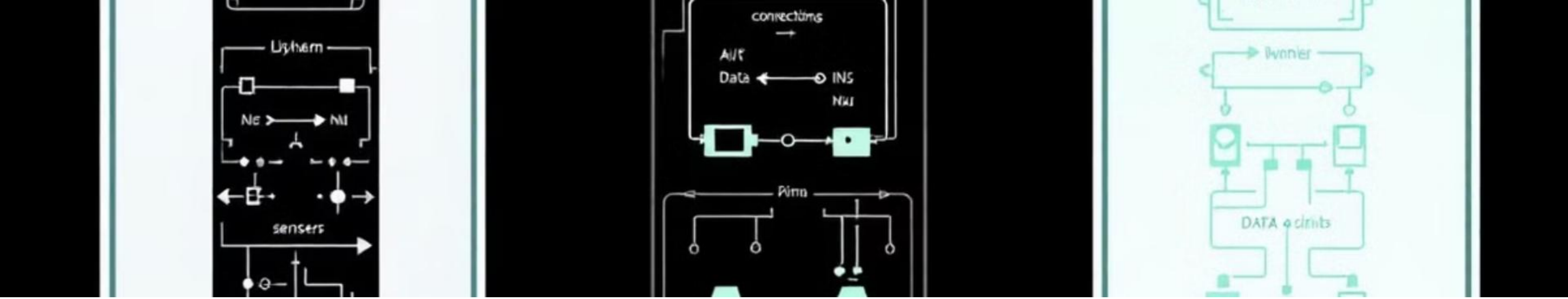
Digital twins provide highly accurate models of battery systems, capturing complex relations between parameters and enabling precise simulations for performance analysis.

2 **Self-Evolving**

Digital twins can learn and adapt based on real-time data, evolving their models to become more accurate and predictive over time, leading to better understanding of battery behaviour.

3 **Secure**

By integrating with robust cybersecurity measures, digital twins can ensure the integrity and security of the battery system's data and operations, protecting sensitive information.




# Digital Twin Background in Li-ion Battery Systems

4

## Faster Prototyping And Redesigning

Digital twins enable fast prototyping and redesigning of battery systems, allowing engineers to test different configurations and materials virtually, reducing time and cost of physical iterations.

5

## Predictive Maintenance

By analyzing real-time data and predicting potential issues, digital twins enable proactive maintenance, reducing downtime, and extending the lifespan of battery systems.

6

## Accessibility

Digital twins provide remote access and monitoring capabilities, enabling engineers and operators to track and analyze battery performance from anywhere, improving operational efficiency and decision-making.

# Digital Twin Architecture for Li-ion Battery Systems

1

## Physical Layer

This layer comprises the actual Li-ion battery system, including its physical components, sensors, and actuators.

2

## Digital Layer

This layer represents the virtual counterpart of the physical battery system, housing data storage, digital models, and analytics capabilities.

3

## Network Layer

This layer connects the physical and digital layers, facilitating seamless data exchange and communication between the battery system and its digital twin.

4

## Service Layer

This layer provides various services for data analysis, visualization, and control, enabling real-time monitoring, diagnostics, and optimization of the battery system.

# Digital Layer: Data Storage

## Cloud Storage

Cloud-based data storage offers scalability, security, and accessibility, allowing for efficient data management and analysis of large datasets generated by battery systems.

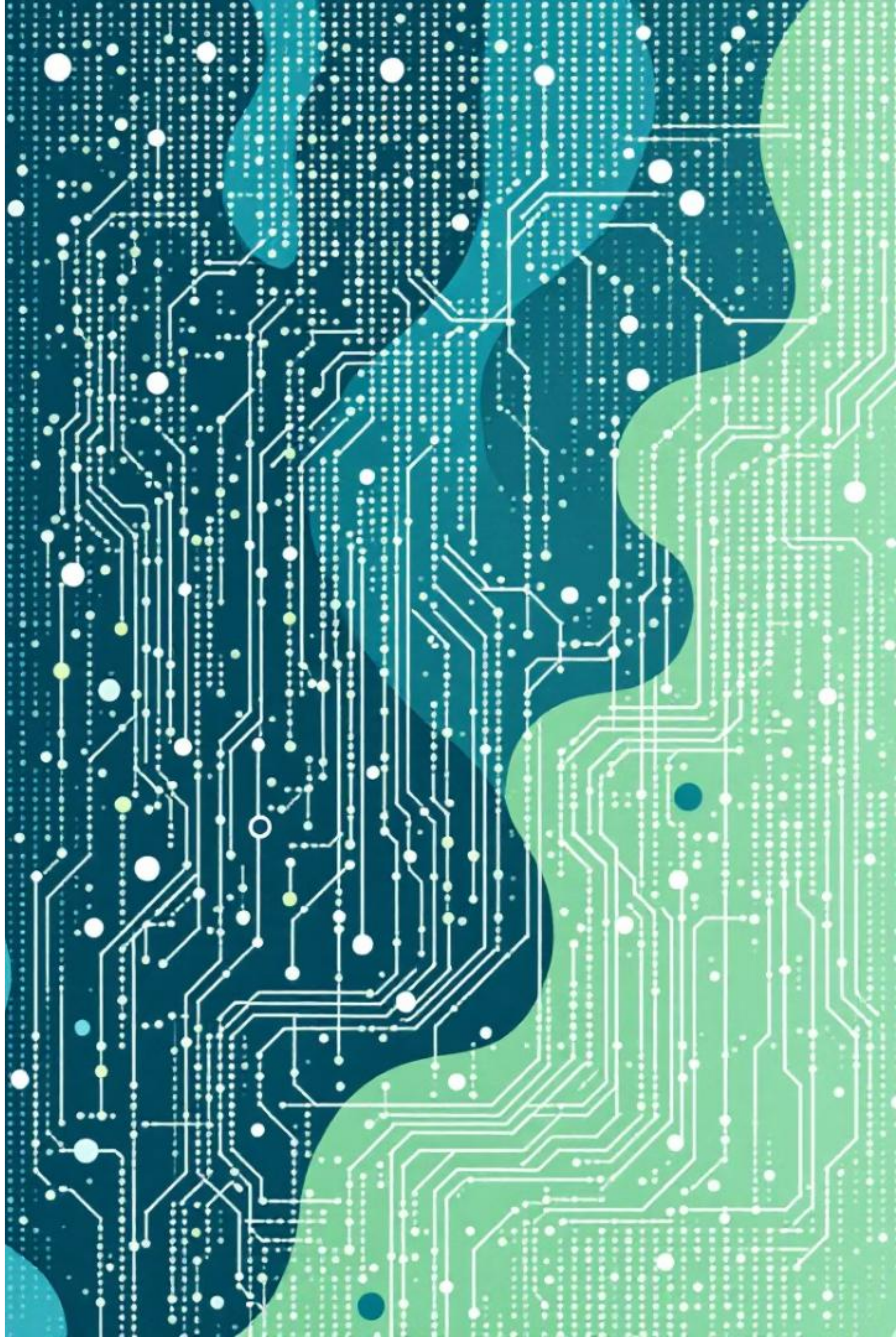
Data is stored in multiple relational databases.

## Data storage

Database 1: Operating Parameters: This database stores data associated with the operational parameters of the Li-ion BESS.

Database 2: Performance Parameters: This database stores data associated with the performance parameters of the Li-ion BESS.

Database 3: Ranges: This database contains the ranges for each operating and performance parameter, specifying acceptable ranges and indicating when actions must be taken to prevent battery degradation.



# Digital Layer: Digital Models

## Geometric Model

This model represents the physical geometry of the battery system, including its components, dimensions, and spatial arrangements, providing a visual representation of the system's structure.

## Behaviour Model

This model simulates the behaviour of the battery system based on its chemical, electrical, and thermal characteristics, providing insights into the system's performance under different conditions.
e.g., Electrochemical Models, Equivalent Circuit Models, Neural Network Models, and Physics-Based Models.

## Data-Driven Models

This model leverages historical and real-time data from the battery system to develop machine learning algorithms that predict future performance, identify anomalies, and optimize operations.

# Network Layer: Connecting the Physical and Digital

1

### Data Acquisition

Sensors in the battery system collect real-time data on various parameters, including voltage, current, temperature, and state of charge.

2

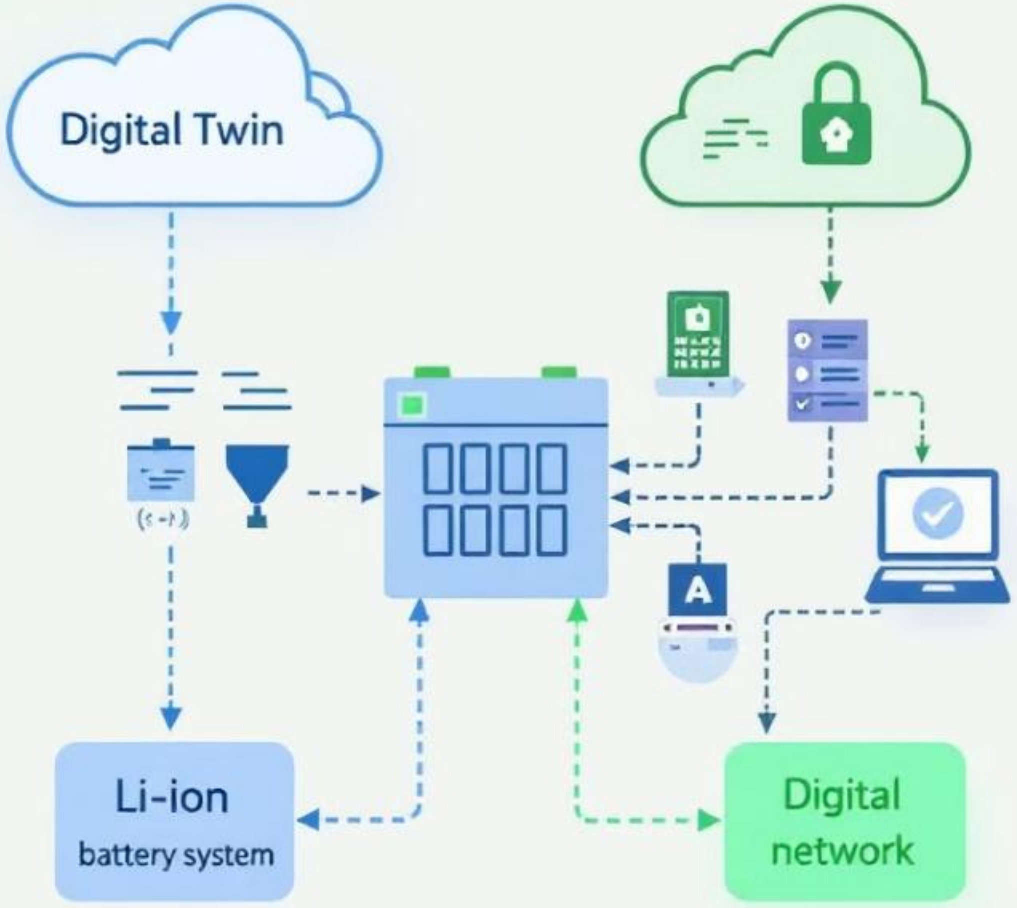
### Data Transmission

Common protocols used in digital twins include Internet, Wireless, and IoT protocols. The choice of protocol depends on the specific requirements of the application, such as data transfer rate, data format, and security features.

3

### Data Integration

The digital twin integrates the incoming data with existing models and analytics, creating a comprehensive representation of the battery system's state.



# Service Layer of Li-ion battery systems (BESS)

## 1

### Monitoring

Real-time monitoring of battery performance, including voltage, current, temperature, and state of charge, providing insights into the system's health and status.

## 2

### Diagnostics

Analysis of data to identify anomalies and potential issues, enabling early detection and prevention of battery degradation or failure.

## 3

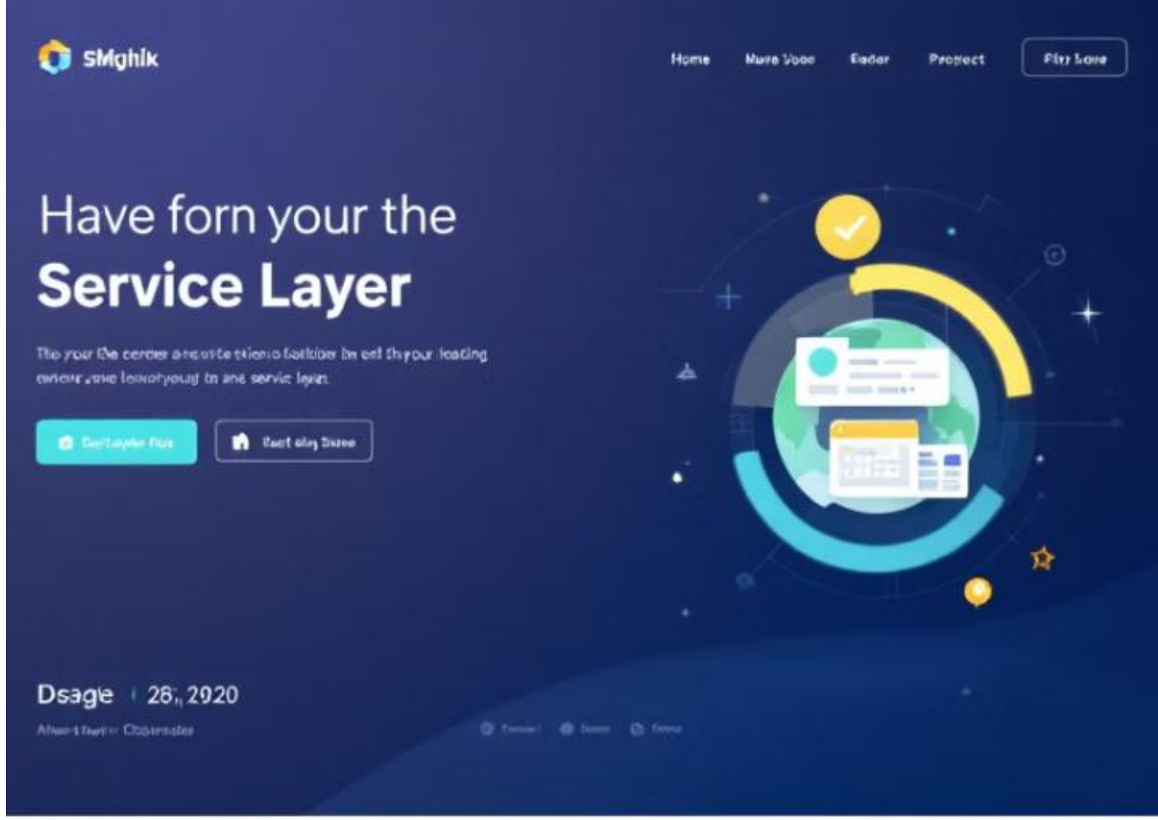
### Optimization

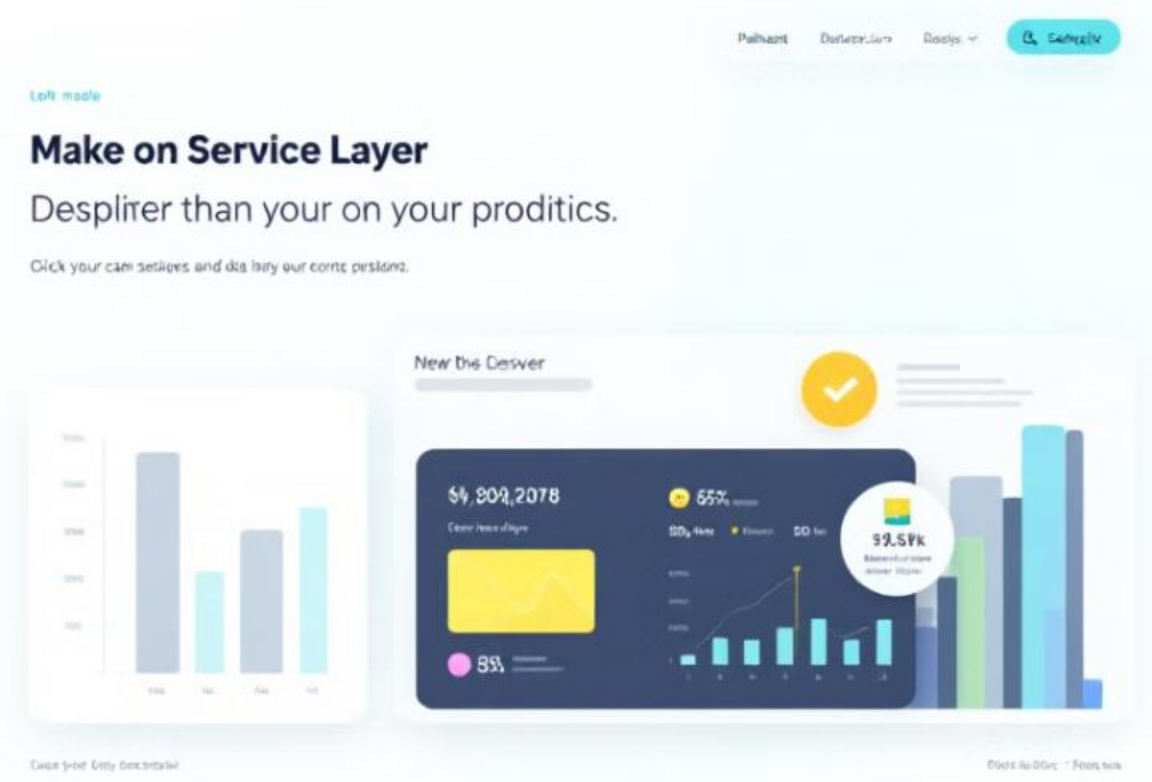
Utilizing data-driven insights to optimize battery charging, discharging, and operational parameters for improved efficiency and lifespan.

## 4

### Control

Remote control and management of battery system operations, allowing for adjustments to charging protocols, discharge rates, and other parameters based on real-time data and analysis.



# Hierarchy of Battery Digital Twins

## Component Twins

Represent individual components within a battery, such as electrodes, separators, and electrolytes. They capture the detailed behavior of each component, providing insights into degradation mechanisms and performance.

## Device Twins

Represent individual battery devices, encompassing multiple components. They aggregate data from component twins to provide a holistic view of device performance, health, and remaining useful life.

## System Twins

Represent the entire battery system, including multiple devices and their interactions. Data is pooled together to increase the predictive capabilities of a single asset and reduce uncertainty.

# Proposed Framework: Battery Digital Twin

The digital twin is a combination of three components:

1. On-Vehicle BMS (physical system)
2. Battery Digital Model (virtual system)
3. Cloud-based interconnection (data link)

1

### Data Preprocessing Approach

Utilizes wavelet transforms for noise reduction and feature extraction, enabling accurate data analysis and model training.

2

### Continual Learning Approach

Adapts the digital twin model to new data and changing conditions, ensuring its accuracy and relevance over time.

3

## Kalman Filter Approach

In the research papers, they propose a Kalman filter technique for SoC estimation that uses a combination of coulomb counting and open-circuit voltage methods to provide a close estimate of the actual value.
The Kalman filter method consists primarily of three steps: prediction, measurement, and updating.

The state estimate and estimate variance matrix be $x_{t-1}$ and $P_{t-1}$ at time $t-1$

$$x_{t-1} = \begin{bmatrix} SoC(\%) \\ Current(I) \end{bmatrix}$$

$$P_{t-1} = \begin{bmatrix} \sigma^2_{estimate} & 0 \\ 0 & \sigma^2_{estimate} \end{bmatrix}$$

$$F_t = \begin{bmatrix} 1 & -\frac{\Delta t}{10800} \times 100 \\ 0 & 1 \end{bmatrix}$$

$$x_t = F_t \begin{bmatrix} SoC(\%) \\ I \end{bmatrix}$$

$$P_t = F_t \begin{bmatrix} \sigma^2_{estimate} & 0 \\ 0 & \sigma^2_{estimate} \end{bmatrix} F_t^T$$

$$\bar{H} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$y_t = \bar{H} \begin{bmatrix} SoC(OCV) \\ I \end{bmatrix}$$

$$\bar{R} = \begin{bmatrix} \sigma^2_{meas} & 0 \\ 0 & \sigma^2_{meas} \end{bmatrix}$$

$$z_t = y_t - \bar{H} x_t$$

$$S_t = \langle \bar{H} | P_t | \bar{H}^T \rangle + \bar{R}$$

The Kalman gain is computed using the residual variance, observation, and prediction variance matrices are given by $K_t$ = $P_t\ H^{-T}\ S_t^{-1}$
Using Kalman gain, the final state estimates $x_t$ and state variance matrices are updated as given in equations below:

$$x_t = x_t + K_t z_t$$

$$P_t = (1 - K_t) P_t$$

# Cloud-Based Battery Management System

### Stationary and Mobile Systems

The system manages both stationary and mobile battery systems, providing comprehensive monitoring and control capabilities.

### BMS-Slave

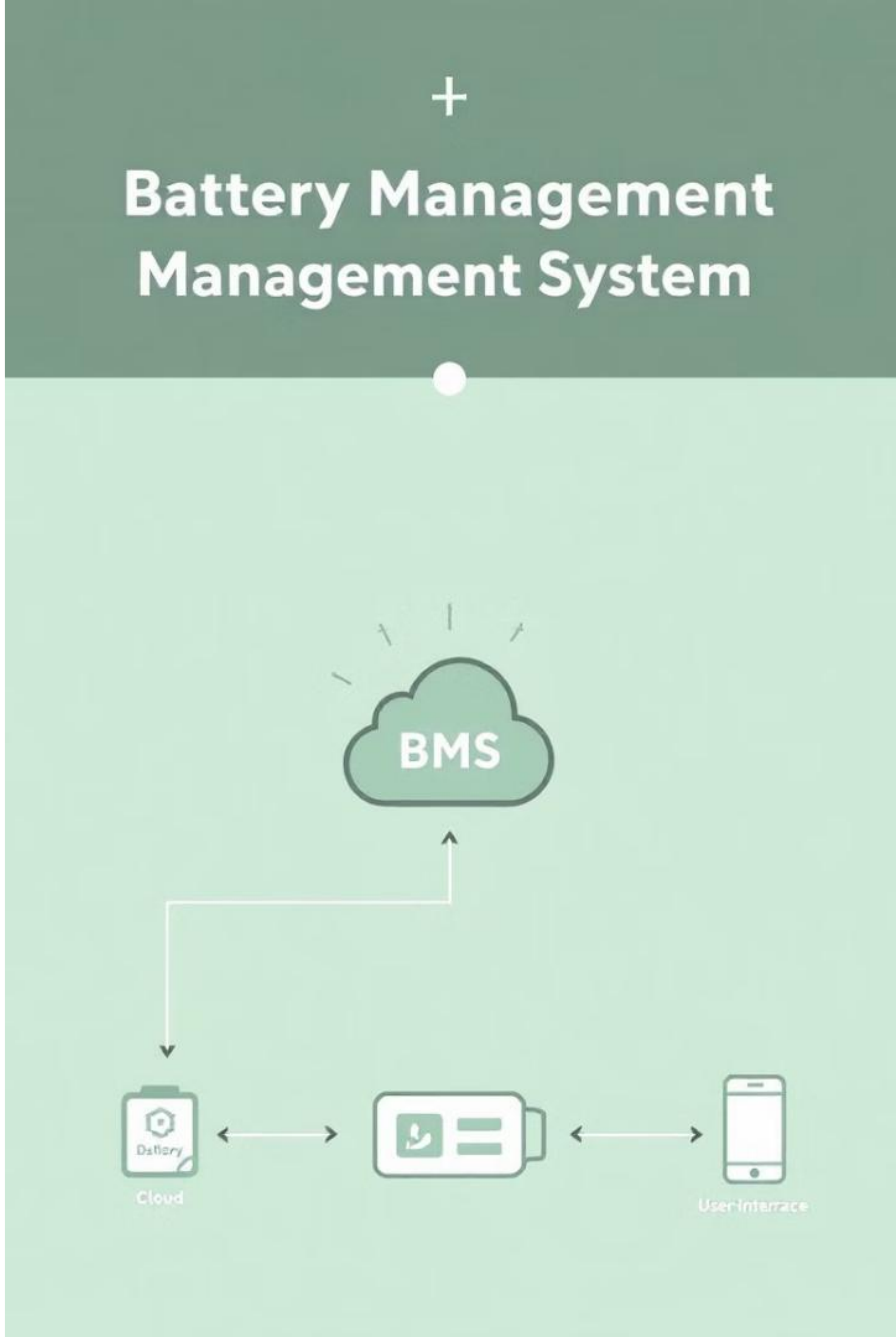
The system includes a battery management system (BMS) slave that collects and transmits real-time data from battery devices.

### IoT Component

An Internet of Things (IoT) component such as Raspberry Pi connects battery devices to the cloud, facilitating data transfer and remote control.

### Cloud Platform

The cloud platform stores and processes data from battery systems, enabling advanced analytics and model training.



# Application Programming Interface (API)

- The API serves as a bridge between the cloud database and data-analytic algorithms.
- It allows for the use of various programming languages, such as MATLAB and Python, to monitor battery states using diagnostic algorithms.
- The API facilitates data visualization in the UI.

# User Interface (UI)

## Real-Time Monitoring

Provides real-time visualization of battery performance, health, and remaining useful life through intuitive dashboards and graphs.

## Data Analysis and Reporting

Enables users to analyze battery data, generate reports, and identify trends, aiding in performance optimization and decision-making.

## Alert and Notification System

Generates alerts and notifications in case of anomalies, critical events, or impending failures, ensuring proactive maintenance and safety.

# Digital Twin Implementation on Cloud

## Continual Learning

The digital twin serves as a virtual representation of a physical battery, capturing its characteristics, behavior, and degradation over time. This real-time data is continuously fed back into the model, allowing for ongoing updates and refinements, improving the accuracy of the digital twin's predictions.

# Impedance Metrology and Calibration

## Realization of Impedance Scales

The realization of impedance scales is essential for accurate impedance measurements.

Impedance standards provide traceable references for calibration and comparison.

## Measuring Impedance of LIBs

Electrochemical Impedance Spectroscopy (EIS) is a technique commonly used to measure the impedance of lithium-ion batteries (LIBs).

It involves applying a small sinusoidal voltage perturbation and measuring the resulting current response.

# EIS Measurement, Interpretation, and Validation

## Measurement Techniques

EIS measurements can be performed in potentiostatic (PEIS) or galvanostatic (GEIS) modes, using different excitation signals (single-sine, multi-sine, or broadband noise) and parameters (frequency range, amplitude, and duration).

## Interpretation

Impedance spectra from EIS can be interpreted using equivalent circuit models (ECMs) or physics-based models. The DRT method transforms impedance data into the time domain, offering insights into battery processes. While conventional ECMs use electrical components to represent impedance, physics-based models rely on electrochemical principles for a more detailed understanding.

## Validation

Validation ensures the accuracy of EIS models through methods like Kramers-Kronig relations, which verify the consistency of impedance data, and postmortem analysis, which examines battery degradation and failure mechanisms. Postmortem techniques include cell inspection, disassembly, and ex situ analysis to assess material performance and identify failure modes.

# Interpretation of EIS Data: Modeling Approaches

### Distribution of relaxation times

The distribution of relaxation times (DRT) method transforms the impedance data from the frequency to the time domain, providing insights into different electrochemical processes within the battery.

### Conventional Equivalent Circuit Modeling

Equivalent circuit models use combinations of resistors, capacitors, and other circuit elements to represent the battery's electrochemical behavior. These models provide a simplified representation of the battery's impedance response but may not capture the underlying physics accurately.

### Advanced Physics-Based Modeling

Physics-based models incorporate detailed knowledge of the battery's electrochemical processes and materials, providing a more accurate and predictive representation of the battery's behavior. However, these models can be more complex to develop and validate.

# Validation of EIS Measurements

1

## Kramers-Kronig Relations

Kramers-Kronig relations are mathematical relationships used to verify the consistency of EIS data, ensuring that the measured impedance values adhere to physical principles. If the data satisfies the Kramers-Kronig relations, it indicates that the measurements are reliable and can be used for further analysis.

$$Z'(\omega) = Z'(\infty) + \frac{2}{\pi} \int_0^\infty \frac{xZ''(x) - \omega Z''(\omega)}{x^2 - \omega^2} dx$$

and

$$Z''(\omega) = -\frac{2\omega}{\pi} \int_0^\infty \frac{Z'(x) - Z''(\omega)}{x^2 - \omega^2} dx$$

2

## Postmortem Analysis

Postmortem analysis involves dismantling the battery and examining its internal components to understand the degradation mechanisms and failure modes. This provides hidden trends about the battery's state of health and can help improve future designs.

# Postmortem Analysis: Cell Inspection and Disassembly

## Cell Inspection

Visual inspection of the battery's external appearance can reveal signs of damage or degradation, such as swelling, corrosion, or leaks. This initial assessment provides valuable clues about the battery's state of health.

## Cell Disassembly

Disassembly involves carefully separating the battery's components, such as electrodes, separator, and electrolyte, for detailed examination. This allows for the identification of specific degradation mechanisms and provides insights into the battery's failure mode.

# Postmortem Analysis: Ex Situ Analysis

## 1

### SEM

Scanning electron microscopy (SEM) provides high-resolution images of the battery's internal structures, revealing details of degradation mechanisms such as cracking, delamination, and particle growth.

## 2

### XRD

X-ray diffraction (XRD) analyzes the crystal structure of battery materials, providing information about phase changes, stress, and the presence of impurities that can contribute to degradation.

## 3

### Other Techniques

A variety of other analytical techniques, such as X-ray photoelectron spectroscopy (XPS), gas chromatography-mass spectrometry (GC-MS), and inductively coupled plasma atomic emission spectroscopy (ICP-AES), can be used to characterize the battery's components in detail.

# State-of-Charge Estimation: Adaptive Extended H-infinity Filter (AEHF)

## Estimation Process

The AEHF utilizes a Kalman filter-based approach to estimate the battery's SOC. It integrates real-time data from battery sensors, such as current and voltage, to calculate the current SOC.

## Prediction Process

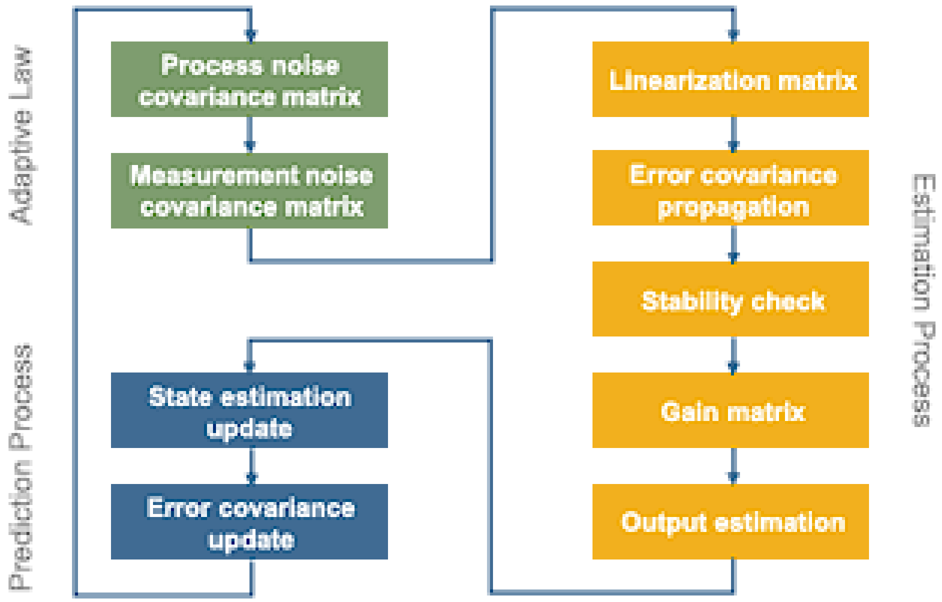
The filter employs a prediction model to forecast the future SOC based on past data and system parameters. This helps anticipate battery behavior and optimize charging and discharging strategies.

## Adaptive Process

The adaptive process enables the AEHF to adjust its parameters in response to changing conditions, such as temperature variations or aging effects. This adaptability enhances the filter's robustness and accuracy in estimating SoC.

# State-of-Charge Estimation with AEHF

H-infinity filters have shown high robustness and are further explored in battery state estimation. The adaptive extended H-infinity filter (AEHF) is an optimal estimator, which can be computed recursively using noisy input data in real-time to analyse and solve a wide class of state estimation problems.




### Real-Time Monitoring

The AEHF provides real-time SOC estimates, allowing for precise battery management and optimization. It helps prevent overcharging and deep discharge, extending the battery's lifespan.

### Performance Optimization

With accurate SOC estimates, the battery management system can optimize charging and discharging strategies. This leads to improved battery efficiency, reduced energy consumption, and enhanced vehicle performance.

1

2

3

### Predictive Maintenance

The AEHF's predictive capabilities enable early detection of battery degradation. By monitoring the SOC estimation accuracy, we can anticipate potential issues and schedule maintenance before failures occur.

# State-of-Health Estimation: Particle Swarm Optimization (PSO)

### Random Initialization

The PSO algorithm begins with a population of potential solutions (particles) initialized randomly within the search space. Each particle represents a possible estimate of the battery's SoH.

### Swarm Evolution

Particles in the swarm iteratively update their positions and velocities based on their own experiences and the experiences of the other particles. This dynamic interaction helps the swarm explore the solution space effectively and converge towards optimal solutions.

# State-of-Health Estimation with PSO

1 Capacity Estimation

2 Internal Resistance Measurement

3 Cycle Life Prediction

The PSO algorithm estimates the battery's SOH by analyzing its capacity, internal resistance, and cycle life. By monitoring these key parameters, we can assess the battery's overall health and anticipate its remaining lifespan.

# Experimental Setup and Validation

## Dataset Description

The dataset used for validation includes a variety of operational data collected from lithium-ion batteries under different conditions. This data encompasses parameters such as voltage, current, temperature, and cycling history.

## Field Validation

Field validation involves testing the cloud BMS in real-world scenarios to assess its performance and reliability. This includes monitoring battery systems in operational environments and comparing the results with expected outcomes.

# Experimental Validation: State of Charge (SoC) Estimation

### Adaptive Extended H-infinity Filter (AEHF)

The AEHF-based SoC estimation algorithm is validated through experiments that compare its estimates with actual SoC measurements. Results demonstrate the algorithm's accuracy and effectiveness in various operating conditions.

# Experimental Validation: State of Health (SoH) Estimation

1

### Particle Swarm Optimization (PSO)

2

### Parameter Optimization

The PSO-based SOH estimation algorithm was employed to estimate the degradation level of the battery. PSO is a metaheuristic optimization technique that utilizes a swarm of particles to find the optimal parameters for the SOH estimation model.

3

### Performance Evaluation

The PSO-based SOH estimation algorithm was evaluated based on its ability to accurately predict the battery's capacity fade and other degradation parameters. The results highlight the algorithm's effectiveness in providing reliable SOH estimates, enabling accurate assessment of battery health.

# Validation Results

## SoC Accuracy

The AEHF algorithm demonstrated high accuracy in SoC estimation, with minimal errors compared to the ground truth values. The algorithm successfully adapted to changes in battery parameters and operating conditions, maintaining accurate SoC estimates even during rapid charge and discharge cycles.

## SoH Prediction

The PSO-based SOH estimation algorithm accurately predicted the battery's capacity fade and other degradation parameters. The algorithm successfully captured the aging effects of the battery, providing valuable insights into battery health and remaining useful life.

# Pipeline Timelines

1

### Phase 1: Data Collection and Preprocessing

This phase involves collecting real-world battery data from an operational electric vehicle and preprocessing the data to ensure accuracy and consistency. This phase is crucial for providing the foundation for algorithm development and validation.

2

### Phase 2: Algorithm Development and Validation

This phase focuses on developing and validating the AEHF and PSO algorithms using the collected dataset. The algorithms are tested and refined to ensure optimal performance in estimating SoC and SoH.

3

### Phase 3: System Integration and Deployment

This phase involves integrating the validated algorithms into the cloud BMS and deploying the system in an operational electric vehicle. This phase includes testing the overall system performance in real-world scenarios.

4

### Phase 4: Evaluation and Optimization

This phase involves evaluating the system's performance in real-world applications and identifying areas for improvement. This phase includes optimizing the system's performance based on the collected data and feedback.

# Future Directions

## Machine Learning

Integrating machine learning techniques into the BMS can enhance predictive maintenance capabilities, enabling proactive identification of potential battery issues and extending battery lifespan.

## Communication Protocols

Developing secure and reliable communication protocols for data transmission between the battery and the cloud server is crucial for ensuring data integrity and system security.

## Battery Chemistry

Further research into advanced battery chemistries can lead to improved energy density, faster charging times, and extended battery life, driving advancements in electric vehicle technology.

# Conclusion

This presentation outlines a comprehensive digital twin framework for Li-ion battery systems, addressing key challenges in monitoring, diagnostics, and predictive maintenance. By integrating advanced algorithms such as AEHF and PSO for SoC and SoH estimation, alongside cloud-based solutions, the framework enhances system reliability, performance, and longevity. The validation results highlight the potential of digital twin technology to revolutionize battery management, paving the way for safer, more efficient, and scalable energy solutions. Future efforts should focus on refining algorithms, incorporating advanced machine learning techniques, and standardizing protocols for broader industrial adoption.