# Life Predication Online Model Using Fine KKN Algorithm for Smart Batteries to Estimate the Accurate Degradation Phase Point in Hybrid Electric Vehicle Application

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***Abstract*: This project uses Arduino Uno and Unity 3D to create a digital twin with IoT capabilities for real-time battery monitoring and lifespan prediction. The system monitors battery metrics including voltage, current, temperature, State of Charge (SoC), and State of Health (SoH) using sensors and an Arduino microcontroller. The obtained data is transmitted to a cloud-based IoT platform via a Wi-Fi module (ESP8266), allowing for real-time remote access. Unity 3D's digital twin simulates the behavior of a real battery, providing interactive display of important parameters and performance trends. Coulomb counting is used to compute SoC, whereas watching the loss of battery capacity over time determines SoH. Predictive analytics are used in the system to predict the battery's remaining useful life (RUL). When performance thresholds are met, alerts and notifications are sent via the IoT dashboard and Unity interface. The digital twin enhances monitoring and enables predictive maintenance, resulting in optimal utilization and preventing unexpected problems. This concept has several applications, including electric cars, renewable energy storage systems, and consumer electronics. This system offers real-time IoT connectivity, 3D visualization, and predictive modeling, making it a powerful tool for battery management, analytics, and health tracking.**

***Keywords*: Digital Twin of li-ion battery, Degradation Point, Internet of Things.**

## 1. Introduction

### *A. Introduction to IoT Enabled Digital Twins for battery*

The increasing reliance on battery- powered systems in industries such as electric vehicles (EVs), renewable energy storage, and consumer electronics needs accurate battery health monitoring and management. Batteries deteriorate over time as a result of repeated charge and discharge cycles, temperature fluctuations, and other environmental conditions. To solve these issues, real-time monitoring and predictive analytics are critical for guaranteeing peak battery performance and extending its longevity.

This paper suggests creating an IoT- enabled digital twin for battery monitoring and lifespan prediction with Arduino Uno and Unity 3D. A digital twin is a virtual simulation of a real-world battery's activity in real time, allowing users to interactively monitor voltage, current, State of Charge (SoC), and State of Health (SoH). The system collects data using sensors linked to an Arduino Uno and transmits it over Wi-Fi (ESP8266/NodeMCU) to an IoT platform for cloud storage and remote access.

### *B. Exploring the role of IoT Enabled Digital Twins*

Digital Twins transforms battery management by integrating real-time monitoring, powerful simulations, and predictive analytics. IoT sensors continually collect important metrics such as voltage, current, temperature, state of charge (SoC), and state of health (SoH), and send this information to a cloud-based platform using efficient communication protocols. A Digital Twin, which functions as a virtual counterpart of the physical battery, combines real-time data with machine learning algorithms and physics-based simulations to anticipate performance, detect deterioration trends, and estimate remaining usable life (RUL). Using this strategy, abnormalities may be recognized early, allowing for proactive maintenance and decreasing unexpected failures. Predictive algorithms optimize charging cycles and use patterns to increase battery life while lowering expenses. The system also includes user-friendly dashboards for displaying real-time information and actionable insights. The Unity 3D model serves as the visual interface for the digital twin, providing graphical feedback on battery status and performance. Predictive algorithms calculate SoC and SoH, while the system also forecasts the remaining useful life (RUL) of the battery based on historical data. Alerts are generated in case of abnormalities or when thresholds are breached, enabling proactive maintenance to prevent failures.

This project offers a comprehensive solution for battery management, diagnostics, and predictive maintenance.

*C. Benefits of the proposed system*

Digital Twin technologies provide a breakthrough solution by allowing for real- time data capture, virtual modeling, and predictive analysis. IoT-enabled sensors can continually monitor critical battery characteristics, whereas Digital Twins simulate and evaluate battery behavior under a variety of scenarios, delivering precise information about performance and deterioration. These technologies handle crucial issues including capacity fading, internal resistance increase, and thermal instability, enabling exact lifetime prediction and proactive maintenance. This integration of IoT and Digital Twin technologies improves energy efficiency, eliminates waste, and promotes long-term battery use in sectors like electric cars, renewable energy storage, and consumer electronics. Its applications include smart grids, electric cars, portable devices, and energy storage systems, where it provides users with better insights and actionable intelligence for battery health optimization.

## 2. Review Of Literature

N Durga et.al (2023). This paper introduces a digital twin framework for the reliability of lithium-ion batteries, focusing on accurate life prediction and reliability evaluation. The study establishes capacity degradation models, stochastic degradation models, and reliability evaluation models to describe battery degradation's randomness. An adaptive evolution method based on Bayesian algorithms is proposed to enhance prediction accuracy, with experimental verification showing that prediction errors can be controlled within approximately 5%.

K Sidahmed et.al (2022). This work proposes a battery digital twin structure designed to accurately reflect battery dynamics in real-time for electric vehicles. The digital twin relies on data-driven models trained on battery evolution data, including a State of Health (SOH) model and a State of Charge (SOC) model, retrained periodically to account for aging effects. The proposed structure is exemplified on a public dataset, demonstrating high accuracy and inference times compatible with onboard execution.

M Reiners et.,al (2022). This study simulates a 1 MWh grid battery system comprising 18,900 individual cells, each represented by a separate electrochemical model, along with thermal management and power electronic converters. Simulations over up to 10,000 cycles and 10 years assess the impact of cell-to-cell variability, thermal effects, and degradation. Findings highlight that variations in degradation rates dominate system behavior over time, and that careful thermal management control can improve overall efficiency by 5 percentage points over on-off methods, increasing total usable energy after 10 years.

A Sinha et.al, (2021). This paper proposes an effective and novel peak extraction method to reduce computation and memory needs for predicting the Remaining Useful Life (RUL) of battery cells in IoT devices. The model operates with minimal external interference, making it suitable for remote operations. Experimental results demonstrate the method's accuracy and reliability, with a correlation of 0.97 between State of Health (SOH) from peak extraction and RUL.

A Sorenson et.al, (2021). This paper presents a comprehensive power consumption model for battery lifetime estimation in Narrowband Internet of Things (NB-IoT) and Long-Term Evolution for Machines (LTE-M) devices. The model is validated through extensive measurements under various traffic patterns and network scenarios, achieving modeling inaccuracies within 5%. Results indicate that, with proper configuration, IoT device battery lifetimes can reach up to 10 years as required by 3GPP standards.

## 3. Experimental Setup

Setting up an IoT-enabled Digital Twin for a battery requires a mix of hardware, software, sensors, and communication protocols to monitor, analyze, and replicate the battery's activity in real time. The following is an overview of a common experimental setup:

*A. Hardware Components*

- Battery: The monitored battery may be a lithium-ion battery from an electric vehicle (EV), renewable energy storage, or industrial equipment.
- IoT Sensors: Voltage and Current Sensors: Used to detect voltage and current at battery terminals during charging and discharging cycles.
- Temperature Sensors: Used for tracking the temperature at various places throughout the battery (e.g., individual cells) in order to prevent overheating.
- State of Charge (SOC) and State of Health (SOH) Sensors: To determine the battery's current charge level and estimate overall health using performance measures.
- Pressure and vibration sensors (optional): These detect any aberrant physical circumstances that can indicate a problem.
- Microcontroller or Edge Device: A microcontroller, such as Raspberry Pi, Arduino, or industrial-grade controllers like the BeagleBone or ESP32, receives sensor data and sends it to a server or cloud platform for processing.
- Communication Infrastructure: Wi-Fi, Bluetooth, and Zigbee: For connecting IoT sensors, microcontrollers, and the cloud or local network. 5G or LoRaWAN (optional) for wide-area network connectivity with big battery fleets or industrial applications.

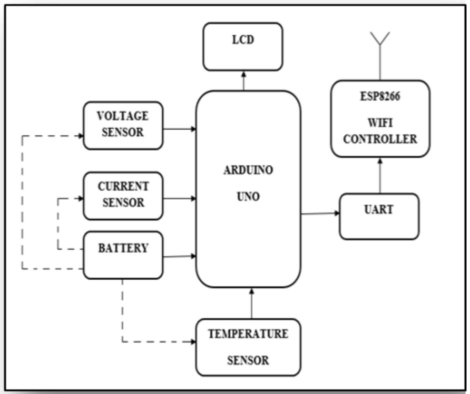


Fig.1. Block Diagram

### B. *Software Components*

- Data collection and management platforms: Such as AWS IoT, Microsoft Azure IoT, and Google Cloud IoT, store and process sensor data locally or in the cloud. This platform takes real-time data, monitors battery health, and archives past data for study.
- Digital Twin program: This program builds a virtual representation of the battery. This might be a custom-built application or software solutions from Siemens Digital Industries, PTC Thing Worx, or Dassault Systems that model and anticipate battery behavior using real-time data. The program uses algorithms to model battery activity, forecast faults, and enhance performance based on sensor data.
- Machine Learning/AI Models (for Predictive Maintenance): Forecast battery health, longevity, and failure points. Models may be developed with platforms such as TensorFlow, Scikit-learn, and other AI tools.
- Visualization Dashboards: A user-friendly interface that present real-time data and insights. Dashboards can display charts, graphs, and notifications about battery health, charge status, temperature, and other performance parameters. Visualization tools include Grafana, Power BI, and bespoke online dashboards.

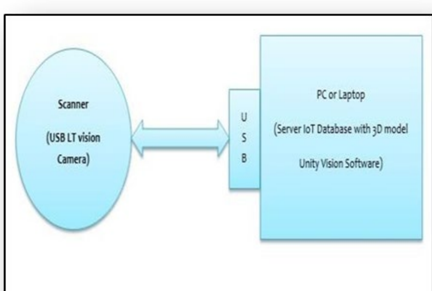


Fig.2. Scanning and Server Database Monitoring Unit

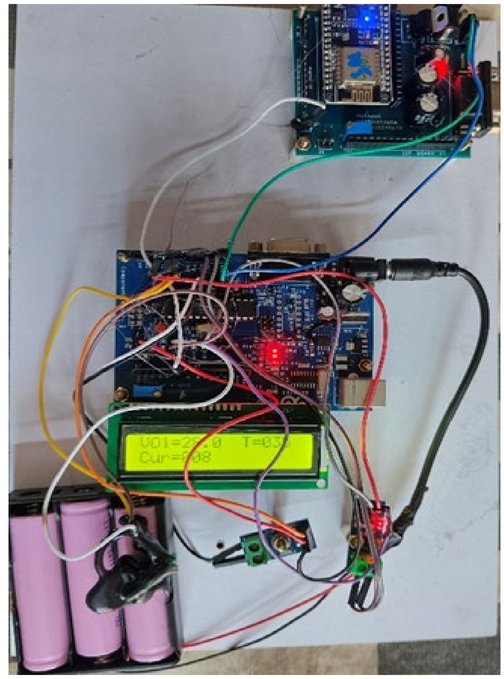

Fig.3. Experimental Setup

### C. *Validation and Testing:*

Validate the Digital Twin's predictions by comparing them to real battery performance data. To enhance accuracy, make necessary adjustments to machine learning models and sensor specifications. Stress the battery testing by submitting it to harsh circumstances (for example, high temperatures and quick charging) to see how well it responds to real-world settings.

### D. *Maintenance and Upgradation:*

Continuously monitor system performance and implement enhancements, such as sensor upgrades, software updates, and Digital Twin model recalibration, to increase predicted accuracy.

## 4. Result and Analysis

The experimental configuration of an IoT-enabled Digital Twin for a battery offers

a strong foundation for monitoring, optimizing, and extending battery life in a variety of applications. This system leads to: Enhanced performance and efficiency through real-time monitoring and improved charging/discharging cycles. Predictive analytics enables proactive maintenance and failure avoidance, resulting in lower expenses for emergency repairs. Extended battery life by monitoring health indicators like State of Charge (SOC) and State of Health (SOH). Energy and cost reductions are achieved through optimal battery utilization and smart charging procedures. By providing these data, IoT-enabled Digital Twins greatly improve battery management, resulting in more sustainable and cost- effective energy solutions.

## 5. Conclusion

IoT-enabled Digital twins for batteries are a revolutionary technique to monitoring, optimizing, and controlling battery systems in a variety of applications, including electric vehicles (EVs), renewable energy storage, and industrial systems. This system provides numerous significant benefits by integrating IoT sensors, real-time data analytics, and predictive algorithms.

- Enhanced Performance Monitoring: Continuous monitoring of battery characteristics such as temperature, voltage, and charge cycles ensures optimal performance and early identification of possible problems, avoiding costly failures.
- Predictive Maintenance: By integrating machine learning and AI, Digital Twins enable predictive maintenance, detecting battery health decline before it leads to failure, limiting downtime, and lowering maintenance costs.
- Battery Optimization: The system may adapt consumption patterns based on real-time data.
- Lifecycle Management: By simulating different situations and projecting the battery's remaining useful life (RUL), Digital Twins make it easier to manage battery replacement and refurbishment schedules, assuring optimal usefulness while eliminating needless replacements.
- Cost Savings and Sustainability: The capacity to optimize battery utilization, eliminate energy waste, and increase battery longevity leads to considerable cost savings and a more sustainable energy strategy.

To summarize, IoT-enabled Digital Twins for Batteries offer a holistic solution for effective battery management, providing vital insights for predictive maintenance, optimization, and overall performance improvement. These solutions not only lengthen battery life, but also improve energy efficiency, reduce operational costs, and promote sustainability in a variety of industries, including electric cars and renewable energy systems.

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