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AI Driven Digital Twin for Improved Battery Performance and Predictive Maintenance

- From Data to insights for faster engineering decisions -

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ABSTRACT: The automotive industry faces significant challenges in managing warranty claims, particularly those related to battery safety in electric vehicles. In 2022 alone, the industry paid $43.1 billion in claims, with a notable portion attributed to battery-related issues. This presentation introduces an AI-powered Digital Twin technology designed to improve battery safety and reduce warranty costs. The Digital Twin leverages data from development, telematics, and in-vehicle usage to provide accurate state-of-health (SOH) monitoring and prediction, anomaly detection, and range optimization. Key benefits include a 97% identification rate of battery issues one month before occurrence, a 92% reduction in recall volume, and three times more accurate range predictions. A reference architecture of the Battery Digital Twin is described, its scalable analytics backend, and the application of machine learning methods for continuous improvement of battery management systems (BMS). This innovative approach not only enhances battery performance and safety but also contributes to sustainable mobility by optimizing operational efficiency and reducing total cost of ownership (TCO)

KEY WORDS: Battery, AI, Digital Twin, Predictive Maintenance, BEV, TCO

1. INTRODUCTION

The mobility sector has seen notable transformations in recent years owing to the rising demand for eco-friendly and sustainable transportation options. In the quest for a greener future, battery electric vehicles (BEVs) have shown considerable growth and emerged as a significant step towards emission-free transport. Nevertheless, these cutting-edge technologies introduce new challenges requiring resolution.

A primary challenge in developing and using battery electric vehicles is mitigating potential errors that might cause extensive problems in the field. As error vulnerability often varies with real-world vehicle usage, traditional validation and error analysis methods are sometimes inadequate. Innovative data analysis techniques that assess and interpret data throughout the entire development process play a vital role in preventing errors effectively.

This article illustrates how combining development process data with field data and artificial intelligence can proactively identify potential issues and devise solutions to enhance the safety and performance of BEVs.

The automotive sector incurs substantial expenses from warranty claims, totaling $43.1 billion in 2022, with a claims rate of 2.1%. Recalls due to risks like fires have led to immense costs, up to $1.8 billion for a single incident. Accurate failure prediction and the application of functional digital twins across the vehicle lifecycle are crucial to reducing these costs.

2. Digital Twin Framework

2.1. Motivation

The introduction of AI-driven digital twins signifies a major advancement in battery safety and management. In the paper it will be shown, how digital twins can transform battery technology, enhancing safety, reliability, and efficiency.

Digital twins offer a dynamic and predictive virtual model of physical systems. When applied to batteries, they enable monitoring, diagnosing, and forecasting potential failures before they occur. This proactive method improves safety protocols by recognizing risks early and facilitating prompt interventions. Moreover, continuous data gathering, and analysis help optimize battery performance and longevity.

By integrating AI with digital twins, the system gains the ability to learn from extensive operational data, which enhances its predictive capabilities over time. This results in more precise simulations and better decision-making processes. For example, AI algorithms can detect patterns and irregularities in battery behavior that could indicate deterioration or impending failure, providing critical insights for preventive maintenance.

Additionally, digital twins aid in developing new battery technologies by allowing researchers to simulate and test different scenarios virtually. This reduces the need for physical prototypes, speeding up research and development while lowering costs and environmental impact.

Our research highlights the significance of a scalable digital twin architecture that adapts throughout the battery lifecycle—from design and manufacturing to operation and beyond. This architecture not only ensures the safety and efficiency of current battery systems but also lays the groundwork for future advancements in energy storage solutions.

2.2. Battery Systems and Vehicle Integration

The integration of battery systems within vehicles necessitates a multidisciplinary approach, ensuring that each subsystem functions harmoniously with others. During the design phase, it is pivotal to consider the thermal management to prevent overheating and ensure optimal performance. Mechanical engineers collaborate to ensure the structural integrity of the battery pack, while software engineers focus on the precision of the BMS.

The data evaluation requirements for these systems are diverse. Mechanical development focuses on strain, vibration, and structural data, whereas thermal systems require precise temperature monitoring and management data. The BMS, which is the brain of the battery system, requires meticulous programming and calibration to accurately interpret data and make real-time decisions.

Moreover, the development of robust monitoring functions within the vehicle requires careful definition of data collection metrics. The BMS must efficiently collect, aggregate, and analyze data, employing statistical methods to derive meaningful insights. These methods include calculations of minimum, maximum, and average values, and the use of histograms to represent data distribution. The challenge lies in achieving a balance between minimizing data transfer and ensuring that all critical measurements related to battery health and performance are captured.

By doing so, the system ensures comprehensive monitoring and enhances data collection efficiency. This approach not only supports current battery technologies but also paves the way for future advancements in energy storage and vehicle integration, ultimately contributing to safer and more efficient battery systems.

2.3 Digital Twin – Introduction

Digital twins support the entire development process. Beginning with a SysML Model as the "Digital Master," Digital Prototypes are created to generate a Scalable Digital Twin. The Digital Master, based on system specifications, validates system design. Digital Prototypes, adapted throughout development, represent precise models of development vehicles but aren't suitable for real-time use with a full customer fleet. Therefore, Scalable Digital Twins are developed to run in the cloud, predicting the behavior of each vehicle in the fleet.

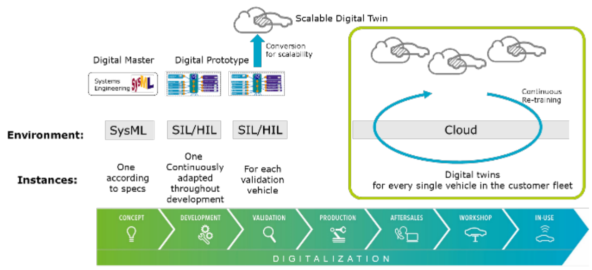

Fig. 2: Functional Digital Twins across the Life Cycle

2.4 Battery Digital Twin – Reference Architecture

Commencing with laboratory data and augmented by in-vehicle usage data, a comprehensive reference architecture was meticulously developed, facilitating the generation and utilization of digital twins. This architecture is composed of four interlinked streams:

1. Load Analysis and Usage-Based Anomaly Detection: This stream is dedicated to identifying usage patterns and detecting anomalies based on load data. Through meticulous analysis of battery usage under varying conditions, potential issues can be identified at an early stage.
2. Cloud-Based State of Health (SOH) Prediction: Utilizing cloud computing capabilities, this stream forecasts the health status of

batteries over time. By processing extensive datasets, it delivers precise SOH estimations, which are essential for effective maintenance and lifecycle management.

3. Channel-Based Anomaly Detection and Behavior Analysis: This stream engages channel-specific data to detect anomalies and scrutinize battery behavior. It aids in comprehending how different channels within the battery system contribute to overall performance and in identifying any irregularities.

4. Data Analytics and Insight Generation: Serving as the core component, this stream integrates all data and analytical insights. It employs Artificial Intelligence (AI) and Machine Learning (ML) models to predict values for various purposes and ensures that the outcomes are accessible to the end user, thereby facilitating data-driven decision-making.

In Figure 1, the interconnection between these streams is depicted. Each module within the architecture incorporates AI or ML models to enhance predictive capabilities. The Data Analytics and Insight Generation stream is particularly critical, ensuring that valuable insights are derived from the data and utilized to inform decisions.

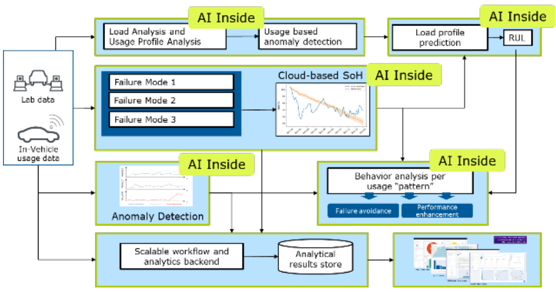

Fig. 2 Digital Twin – Reference Architecture

3. AI Applications

3.1. AI driven Usage Space Analysis

Analyzing fleet data allows the establishment of target vehicle usage parameters, differentiating between typical and extreme usage profiles. This process aids in comprehending customer usage patterns and refining requirements for quality and cost management. A comprehensive methodology was devised to analyze fleet data for defining and optimizing vehicle usage parameters and requirements. It starts with inputting various fleet data such as vehicle types and environmental conditions like weather and temperature. Key parameters are identified, focusing on damaging and aggravating operating conditions, such as high or low load operations, transient idling, and the impacts of fuel and oil quality. These are further refined by considering primary vehicle-level influences, including power requests and operating time, as well as specific metrics like vehicle speed, brake activity, and environmental factors such as temperature and humidity. Vehicle Usage Parameters (VUP) are calculated over each duty cycle by aggregating data from different operational events, facilitating a detailed analysis of vehicle performance over time. This process enables the differentiation of standard and extreme usage patterns, illustrated through scatter plots that differentiate typical and extreme users. Moreover, a similarity analysis groups vehicles based on usage patterns, allowing for optimized requirements in terms of both quality and cost. The key benefits of this approach include gaining insights into regional differences in customer usage (e.g., China versus Europe), quantifying extreme users, and developing optimized design requirements that balance quality with cost efficiency.

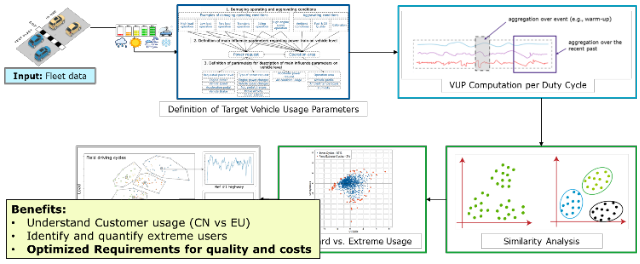

Fig. 3 Usage Space Analysis

3.2. AI driven SOH Estimation and Prediction

With the onset of production and sale of battery electric vehicles (BEVs), there is significant interest in monitoring the battery's state of health (SOH) and detecting abnormal behavior in the battery system. Evaluating a battery's current status involves its performance, internal resistance, and remaining capacity. Through vehicle connectivity, this data is sent to the cloud environment where ML algorithms are employed for analysis across the entire vehicle fleet. Neural networks (NN) help predict the remaining lifespan of individual batteries, requiring extensive data for training. To enhance analysis quality, development phase data like cell and pack tests are also utilized. The development results must be processed on the same data platform as customer fleet data, facilitating comparisons among test benches, pre-series vehicles, and customer vehicles while employing modern techniques like "Transfer Learning" (TL).

Using knowledge from test bench datasets for the customer fleet reduces the necessary data volume. Cloud-based monitoring and fleet-wide analysis enable rapid assessment of individual battery behavior and deviations from typical fleet behavior, allowing prompt countermeasures such as temperature regulation during charging. Main influencing factors learned can determine the current State of Health (SoH) and predict each battery pack's remaining lifespan, permitting recommendations for efficient use and extended durability.

Data analyzed comes from advanced laboratory equipment simulating a busy urban roadway with multiple vehicles, reflecting real-world conditions and variability of these systems. The key message is that transfer learning can reduce prediction errors by more than 30%, suggesting that insights from one domain can effectively improve performance and accuracy in related tasks, leading to more reliable automotive system predictions.

4. CONCLUSIONS

The Paper provides a comprehensive overview of the advancements and applications of AI-powered digital twins for battery systems. The primary objective of this initiative is to enhance battery safety and reduce warranty claims, which have significant cost implications for OEMs worldwide. The presentation highlights the potential for cost savings by accurately predicting failures and reducing recall volumes1.

The digital twin technology involves creating a scalable digital twin for every vehicle in the customer fleet. This includes continuous adaptation throughout the development process and the use of telematics data for scalable analytics. The implementation of the battery digital twin has shown promising results, including a 97% identification rate of battery issues one month before they occur, a 92% reduction in recall volume, and three times more accurate range predictions.

The presentation emphasizes the use of AI and machine learning methods, such as transfer learning, to improve the accuracy of state-of-health (SOH) predictions and anomaly detection. This approach has reduced errors by over 30% and identified potential failures months before they occur. The digital twin technology is applied across various stages of the battery lifecycle, from development to in-vehicle usage. The presentation also discusses the potential for continuous updates of battery management system (BMS) parameters to extend battery life and optimize performance.

In conclusion, the AI-powered digital twin technology for batteries presented by Gerhard Schagerl offers significant advancements in battery safety, cost savings, and performance optimization. The successful implementation of this technology can lead to substantial improvements in the automotive industry, particularly in the areas of warranty cost reduction and enhanced customer satisfaction.

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