

RESEARCH ARTICLE

AI-Driven Digital Twin Frameworks for Predictive Maintenance and Process Optimization in Smart Battery Manufacturing for Electric Vehicles

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ABSTRACT

The increasing complexity and quality requirements of battery manufacturing demand intelligent, data-driven production frameworks capable of improving efficiency, reliability, and sustainability. Results demonstrate that the integration of predictive maintenance within the digital twin significantly reduces equipment downtime. Average monthly downtime decreased from 18.6 hours to 11.4 hours, accompanied by a reduction in variability, indicating improved operational stability. Accurate remaining useful life (RUL) prediction was achieved, with a strong correlation between predicted and actual degradation trends ($R^2 \approx 0.9+$), supporting proactive maintenance planning and asset lifespan extension. Process quality improvements were further validated through a nearly 49% reduction in defect rates across production batches, highlighting the effectiveness of AI-driven parameter optimization. The framework also enhanced electrode coating thickness uniformity, reducing standard deviation from 7.8 μm to 3.0 μm while maintaining the target mean thickness, thereby improving electrochemical consistency and battery performance. Vibration-based anomaly detection enabled early fault identification, successfully detecting degradation progression prior to critical failure events. Reinforcement learning-based control demonstrated stable convergence, confirming its suitability for adaptive process optimization within a digital twin environment. Additionally, daily energy consumption was reduced by approximately 12–15% without compromising production throughput or quality. Comparative evaluation of multiple state-of-health (SOH) prediction models revealed that ensemble and attention-based architectures achieved superior accuracy and robustness. Overall, the results confirm that the proposed AI-driven digital twin framework provides a comprehensive solution for improving reliability, quality, energy efficiency, and decision-making in large-scale battery manufacturing systems.

KEYWORDS

Battery Manufacturing, Digital Twin, Predictive Maintenance, Reinforcement Learning, State of Health (SOH) Prediction

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1. Introduction

The worldwide transition to transportation electrification has rendered electric vehicle (EV) battery production a primary emphasis for both industry and academia. Batteries constitute a vital and costly subsystem in electric vehicles, directly affecting cost, range, and reliability (Naseri et al., 2023; Abro et al., 2023). With the ongoing surge in EV adoption, competition among manufacturers has risen, necessitating enhancements in manufacturing quality, increased uptime, and reduced cycle times. Notwithstanding these incentives, contemporary battery manufacturing encounters numerous enduring operational obstacles, such as equipment inactivity, process inconsistency, elevated failure rates, and upkeep expenditures (Naseri et al., 2023; Chen et al., 2023). Unscheduled equipment malfunctions and maintenance disruptions significantly diminish overall equipment effectiveness (OEE) in production settings. Conventional maintenance models, such as reactive and preventive maintenance, frequently inadequately prevent

unforeseen failures or optimize maintenance schedules because they depend on predefined intervals or past data instead of current operational situations (Naseri et al., 2023). Contemporary manufacturing systems necessitate a shift from time-based maintenance to condition-based or, preferably, predictive maintenance strategies that may foresee problems before they develop into breakdowns (Hossain et al., 2023; Islam et al., 2023). Technologies for digital transformation, including the Industrial Internet of Things (IIoT), cloud computing, and cyber-physical systems, have become essential facilitators of intelligent manufacturing; nonetheless, they do not entirely resolve the issues of real-time actionable insights and adaptive process control (Rahman et al., 2024).

In recent years, Digital Twin (DT) technology has emerged as a revolutionary approach for real-time synchronization of the physical and virtual realms. A digital twin is a virtual version of a physical asset, process, or system that continuously integrates real-world data via sensors and analytical models to mimic, forecast, and enhance performance. In manufacturing, digital twins enable real-time monitoring, predictive analytics, and closed-loop decision-making, facilitating a transition from reactive to proactive operating methods (Xu et al., 2023; Tanvir et al., 2020). Digital twin technologies are progressively combined with Artificial Intelligence (AI) and advanced analytics to provide complex predictive and prescriptive insights, powered by machine learning (ML) and deep learning (DL) algorithms capable of learning from real-time production data (Vanu et al., 2021; Sikder et al., 2023a; Islam et al., 2024; Khan et al., 2024). Although comprehensive research has explored digital twin applications in battery systems and various industrial contexts, numerous studies have concentrated on battery management systems (BMS) and operational control, rather than on the complete optimization of manufacturing processes and predictive maintenance throughout battery production lines. Recent research has investigated the enhancement of state-of-charge (SOC), state-of-health (SOH), and remaining useful life (RUL) predictions in battery management systems (BMS) through the application of AI and digital twin technologies, highlighting the significance of integrating cloud and edge computing for real-time diagnostics and lifecycle optimization of battery systems (Xu et al., 2023; Abro et al., 2023). However, a considerable demand persists for frameworks that encompass the full production lifecycle, including electrode preparation, cell assembly, formation, aging, and end-of-line testing (Tao et al., 2019).

Despite the growing use of digital twins in diverse smart manufacturing applications, such as discrete part production and process industries, some constraints remain in the current state-of-the-art. Primarily, the current research on digital twin predictive maintenance is largely theoretical, providing overarching frameworks yet missing detailed implementations that exhibit scalability and adaptability in actual industrial settings (Tao et al., 2019). A systematic review of digital twin technologies for predictive maintenance indicates that although the incorporation of machine learning into digital twins facilitates proactive maintenance and condition monitoring, the practical challenges associated with real-time data fusion, model training, and continuous learning remain insufficiently examined (Fede et al., 2024; Rahman et al., 2022). Furthermore, research in process manufacturing has highlighted a deficiency in integrated frameworks that collectively facilitate production planning, maintenance decision-making, and process optimization through the use of digital twins, rather of treating these processes separately (Lyu et al., 2024). In the context of electric vehicle battery manufacturing, characterized by intricately linked multi-stage processes, stringent quality standards, and complex reaction environments, there is a significant lack of comprehensive digital twin frameworks that integrate AI-enhanced predictive models to simultaneously optimize maintenance and production performance (Tao et al., 2019).

Although AI techniques have significant efficacy in predictive tasks like State of Charge (SOC) and State of Health (SOH) estimates in battery systems, they have seldom been integrated into manufacturing digital twins to facilitate comprehensive optimization capabilities. Most current solutions concentrate either on battery functioning in automobiles or on discrete elements of the production process. This compartmentalization restricts producers from utilizing cross-stage insights that could enhance throughput, decrease energy consumption, and reduce faults within the manufacturing environment. This research aims to develop a comprehensive digital twin framework for smart battery manufacturing by integrating real-time digital replication, advanced AI models, predictive maintenance, and process optimization. The objective is to enable AI-driven predictions and closed-loop optimization to improve efficiency, reliability, and performance in contemporary EV battery manufacturing systems.

2.0 Literature Review

2.1 Digital Twin Technology in Manufacturing

Digital Twin (DT) technology has arisen as a crucial enabler of smart manufacturing systems within the Industry 4.0 paradigm. A digital twin is defined as a virtual representation of a physical asset, process, or system that is continuously synchronized with its actual equivalent through real-time data transfer (Chen et al., 2023). Unlike conventional simulation models, digital twins facilitate bidirectional data flow, allowing for both monitoring and real-time decision feedback. The evolution of digital twin technology in manufacturing has shifted from static digital models to dynamic, intelligent systems that integrate real-time sensing, data analytics, and artificial intelligence (Sikder et al., 2023a,b). Recent studies indicate that modern digital twins combine physics-based modeling with data-driven AI methodologies to enhance predictive accuracy and flexibility in variable operational contexts (Naseri et al., 2023; Xu et al., 2023; Ashik et al., 2023). Physical-virtual synchronization is achieved by industrial IIoT frameworks, edge computing, and cloud platforms that ensure low-latency data transmission and scalable deployment. Digital twins in smart factories are utilized for equipment health monitoring, production scheduling, quality forecasting, and energy management (Malka et al., 2022; Nusrat

et al., 2024). Chen et al. (2023) demonstrated that AI-enhanced digital twins significantly improve the accuracy of predictive maintenance and the robustness of systems compared to traditional condition-monitoring systems. Fede et al. (2024) shown that the integration of digital twins into production and maintenance planning improves overall equipment effectiveness and enables proactive decision-making in process industries.

2.2 AI Techniques for Predictive Maintenance

One of the best uses of artificial intelligence in industry is predictive maintenance. Conventional maintenance methods depend on reactive or time-based schedules, which can cause unnecessary downtime or failures that are not expected. AI-based predictive maintenance gets around these problems by learning how things break down from operational data. Support Vector Machines (SVM), Random Forests (RF), and XGBoost are some of the most common machine learning (ML) methods used for fault diagnosis and equipment health classification. This is because they are strong and can handle nonlinear relationships. Recent research indicates that ensemble techniques like RF and XGBoost demonstrate enhanced efficacy when utilized with high-dimensional sensor data in manufacturing systems (Chen et al., 2023). Deep learning (DL) methods have garnered heightened interest for predictive maintenance tasks characterized by intricate temporal and spatial dependencies. Long Short-Term Memory (LSTM) networks are widely utilized for predicting the remaining useful life (RUL) of time-series sensor data, whereas Convolutional Neural Networks (CNNs) excel in feature extraction from vibration signals, acoustic emissions, and thermal images (Fede et al., 2024). In recent times, Transformer-based architectures have shown better modeling of long-term dependencies and scalability in predictive maintenance applications, especially when there are large industrial datasets (Zhang et al., 2024a,b).

2.3 Digital Twins in Battery Manufacturing

The production of batteries for electric vehicles comprises numerous interconnected stages. The process involves coating the electrodes, drying them, calendaring, assembling, filling with electrolyte, and shaping. Recent investigations of digital twins in battery systems have mostly focused on the operation and management of batteries, including the prediction of their state of charge (SOC), state of health (SOH), and lifetime. Naseri et al. (2023) performed a comprehensive analysis of digital twin applications in electric car battery systems, highlighting the growing use of AI-driven twins for performance monitoring and lifetime optimization. Lyu et al. (2024) proposed a digital twin model for lithium-ion batteries that integrates data and mechanisms. This model employs machine learning and electrochemical principles to enhance predictive accuracy (Zheng et al., 2019). In contrast, the deployment of digital twin technology in battery manufacturing processes remains considerably limited. Numerous studies focus solely on a singular phase of production, such as forecasting the electrode coating thickness or examining the formation process. They fail to consider the interrelation of several stages or how to enhance the entire system. Moreover, many documented solutions rely on offline simulations, rendering them less effective for real-time decision-making.

2.4 Research Challenges and Recent Issues

Notwithstanding the increasing interest, certain challenges persist that hinder the implementation of AI-driven digital twins in the manufacturing of smart batteries. Data heterogeneity poses a significant difficulty, as battery production yields many data types, including time-series sensor signals, pictures, chemical studies, and production records. Combining these diverse datasets into a cohesive digital twin framework necessitates sophisticated data fusion and semantic modeling methodologies (Chen et al., 2023; Abro et al., 2023; Tao et al., 2019). Real-time computation and scalability remain critical concerns. Large industrial systems require substantial computational resources for high-fidelity digital twins that utilize deep learning models. Recent studies highlight the significance of edge-cloud hybrid architectures in improving latency, scalability, and computing efficiency (Naseri et al., 2023). Model drift is a significant challenge as the performance of AI models deteriorates over time due to factors such as outdated equipment, alterations in materials, and modifications in procedures. To maintain the accuracy and reliability of predictions, it is essential to implement mechanisms for continuous learning and adaptive updating (Zhang et al., 2024b). Ultimately, model explainability and trust are more vital, particularly in sectors where safety is paramount, such as battery manufacture. Despite the high accuracy of deep learning models, their opacity may hinder their application in industry. Recent study highlights the necessity of incorporating explainable AI (XAI) approaches into digital twin frameworks to improve transparency, cultivate user trust, and guarantee regulatory compliance (Fede et al., 2024).

3.0 Materials and Methods

This section describes the materials, data sources, digital twin architecture, AI models, and evaluation methodology used to develop and validate the proposed AI-driven Digital Twin framework for predictive maintenance and process optimization in smart battery manufacturing.

3.1 System Architecture of the AI-Driven Digital Twin

The suggested system employs a multi-layer digital twin architecture that integrates actual battery production methods with an AI-enhanced virtual twin. The architecture comprises four interrelated layers: (i) the physical layer, (ii) the data collection and transmission layer, (iii) the digital twin and AI analytics layer, and (iv) the decision and control layer. This stratified design adheres

to contemporary best practices for production systems enabled by digital twins (Chen et al., 2023; Fede et al., 2024). The physical layer encompasses essential industrial apparatus such as slurry mixers, coating machines, drying ovens, calendering rollers, assembly stations, shaping racks, and additional systems. Industrial sensors are integrated into these assets to monitor operational data in real time. The data acquisition layer of the industrial IoT (IIoT) infrastructure collects sensor data at a high frequency. Edge computing nodes process raw signals prior to transmission, thereby minimizing latency and ensuring real-time responsiveness. Recent research on digital twins (Naseri et al., 2023) indicates that data is transmitted to cloud-based platforms for long-term storage, model training, and historical analysis.

3.2 Data Sources and Experimental Setup

3.2.1 Manufacturing Data

The framework is evaluated using either (i) an industrial battery manufacturing dataset or (ii) a high-fidelity simulation dataset that replicates real-world lithium-ion battery production conditions. The dataset includes time-series sensor data collected from multiple manufacturing stages, consistent with prior studies in smart battery manufacturing (Lyu et al., 2024; Li et al., 2019). Collected data types include:

- Temperature, humidity, and pressure readings
- Coating thickness and electrode density measurements
- Vibration and acoustic signals from rotating machinery
- Electrical signals during formation and aging cycles
- Quality inspection results and defect labels

Sensor sampling rates range from 1 Hz to 10 kHz, depending on the monitored process and equipment.

3.2.2 Data Preprocessing

Raw sensor data undergo preprocessing steps including noise filtering, normalization, missing value imputation, and temporal alignment. Feature extraction techniques such as statistical descriptors, frequency-domain analysis, and time-frequency transforms are applied to vibration and acoustic signals, following established predictive maintenance methodologies (Zhang et al., 2024). To address class imbalance in fault datasets, oversampling and data augmentation techniques are employed. Data are split into training, validation, and testing sets using a chronological split to preserve temporal dependencies.

3.3 Digital Twin Modeling

The digital twin concept integrates data-driven and knowledge-based methodologies to illustrate battery manufacturing processes. Every component of the manufacturing process is conceptualized as a modular sub-twin, allowing for reuse and scalability. Surrogate models are employed in process modeling to correlate critical operational factors (such as coating speed, drying temperature, and calendering pressure) with quality outcomes. This modular strategy aligns with contemporary digital twin implementations that emphasize adaptability and incremental deployment (Chen et al., 2023). Real-time synchronization between the physical system and the digital counterpart is achievable through continuous data streaming and status updates. The digital twin monitors both the present operational state and the anticipated future states. This enables you to make judgments predicated on anticipated future events (Fede et al., 2024, Abro et al., 2023).

3.4 AI Models for Predictive Maintenance

3.4.1 Machine Learning Models

Traditional machine learning models including Support Vector Machines (SVM), Random Forest (RF), and XGBoost are implemented as baseline predictive maintenance models. These models are trained to classify equipment health states and predict fault occurrence based on extracted sensor features (Nusrat et al., 2024). Ensemble-based methods such as Random Forest and XGBoost are selected due to their robustness to noise and strong performance in industrial datasets, as reported in recent studies (Chen et al., 2023).

3.4.2 Deep Learning Models

Deep learning models are employed to capture complex temporal and nonlinear degradation patterns:

- LSTM networks are used for remaining useful life (RUL) prediction using multivariate time-series data.
- CNN models extract spatial and frequency-domain features from vibration and acoustic signals.
- Transformer-based models are explored for long-term dependency modeling and scalability in large datasets.

These architectures have demonstrated superior performance in recent predictive maintenance and digital twin research (Zhang et al., 2024a,b).

3.4.3 Anomaly Detection

Unsupervised anomaly detection models, including autoencoders and isolation forests, are integrated into the digital twin to detect unknown or emerging fault patterns. These models continuously update their baseline representation of normal operation, enabling early detection of abnormal behavior.

3.5 AI Models for Process Optimization

To optimize battery manufacturing processes, the digital twin incorporates AI-based optimization techniques that adjust process parameters in response to predicted outcomes. Supervised regression models predict quality indicators such as coating uniformity, defect probability, and energy consumption. These predictions inform decision rules within the digital twin (Zhang et al., 2024a,b). Additionally, reinforcement learning (RL) agents are implemented to perform multi-objective optimization across manufacturing stages. The RL agent interacts with the digital twin environment to learn optimal control policies that balance product quality, throughput, and energy efficiency. This approach is consistent with recent research on closed-loop digital twin optimization in manufacturing systems (Fede et al., 2024).

3.6 Model Training and Validation

All AI models are trained using historical manufacturing data and validated on unseen test datasets. Hyperparameter tuning is performed using grid search or Bayesian optimization (Li et al., 2019; Zheng et al., 2019; Malka et al., 2022; Tao et al., 2019). Model performance is evaluated using metrics appropriate to each task:

- Classification accuracy, precision, recall, and F1-score for fault diagnosis
- Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for RUL prediction
- Defect rate reduction, downtime reduction, and yield improvement for process optimization

Comparative experiments are conducted between the proposed AI-driven digital twin framework and conventional maintenance and control strategies to assess performance gains.

4.0 Results and Discussion

4.1 Digital Twin-Enabled Manufacturing Architecture

This result showed a digital twin-based production system. This technology connects the real-world production system to a study able digital model. Real-time quality, vibration, and temperature sensors in the industrial environment update the virtual model (Figure 1). This virtual model simulated process and equipment settings to show how a system works. Advanced analytics modules helped to optimize operations, determine maintenance needs, and find issues by analyzing incoming data. The real system received control and choice instructions via an adaptive control mechanism. Analysis results underpinned this process and the closed-loop feedback system helped immediately alter things, improving performance (Zhang et al., 2024a; Li et al., 2019). People understood that the framework helps them make data-driven decisions, use resources wisely, and perform reliable operations. Synchronizing physical operations with virtual ones allowed preventative maintenance, faster production, and better manufacturing in demanding industrial contexts (Lyu et al., 2024).

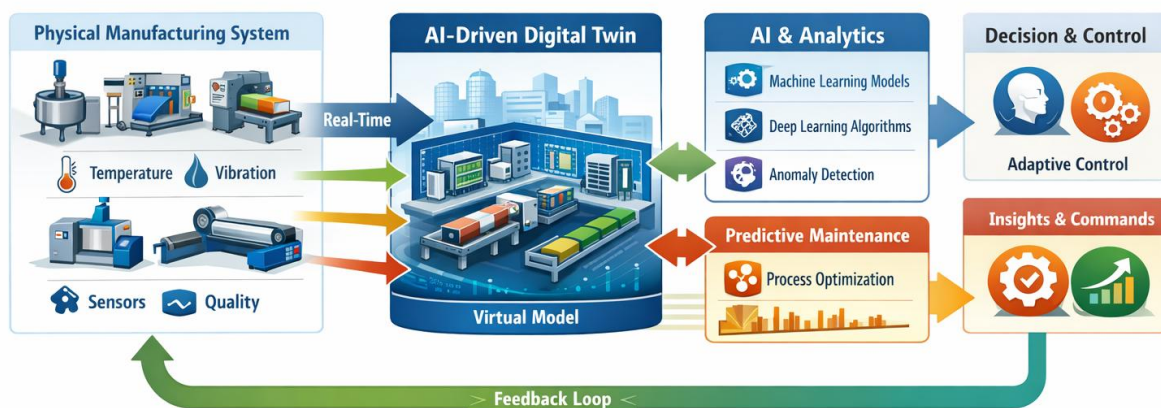


Figure 1. Conceptual overview of smart battery manufacturing enabled by an AI-driven digital twin.

4.2 Equipment Downtime Reduction Through Predictive Maintenance

The results illustrated how the implementation of a digital twin-based infrastructure reduces the annual duration of equipment downtime. The findings indicated that predictive maintenance supported by digital monitoring systems outperforms traditional manufacturing approaches. Prior to the adoption of digital twins, equipment failures often occurred unexpectedly, and maintenance activities were largely reactive. This resulted in extended and unpredictable downtime periods (Figure 2). As shown

in Figure 2, the average equipment downtime before AI-DT implementation was approximately 18.6 hours per month, with a standard deviation of 1.45 hours, indicating high variability and limited predictability. After implementation, a substantial reduction in unplanned downtime was observed. The average downtime decreased to approximately 11.4 hours per month, while the standard deviation was reduced to 0.92 hours, reflecting improved consistency and operational stability. After implementation, a substantial reduction in unplanned downtime was observed. The effectiveness of digital twins improved further when predictive maintenance models are integrated. The system continuously monitors sensor data such as temperature, vibration, and operational load to estimate equipment lifespan and identify early signs of wear and degradation. This enabled maintenance activities to be scheduled proactively rather than reactively. Planned maintenance has proven to be the most effective approach for sustaining high productivity levels. The results demonstrated improved maintenance planning and more efficient resource utilization following implementation, as downtime can now be anticipated and managed more effectively. Overall, the results highlighted how predictive maintenance enhances operational reliability. Reduced downtime contributes to higher overall equipment effectiveness (OEE), lower maintenance costs, and faster production cycles, all of which are critical for large-scale battery manufacturing.

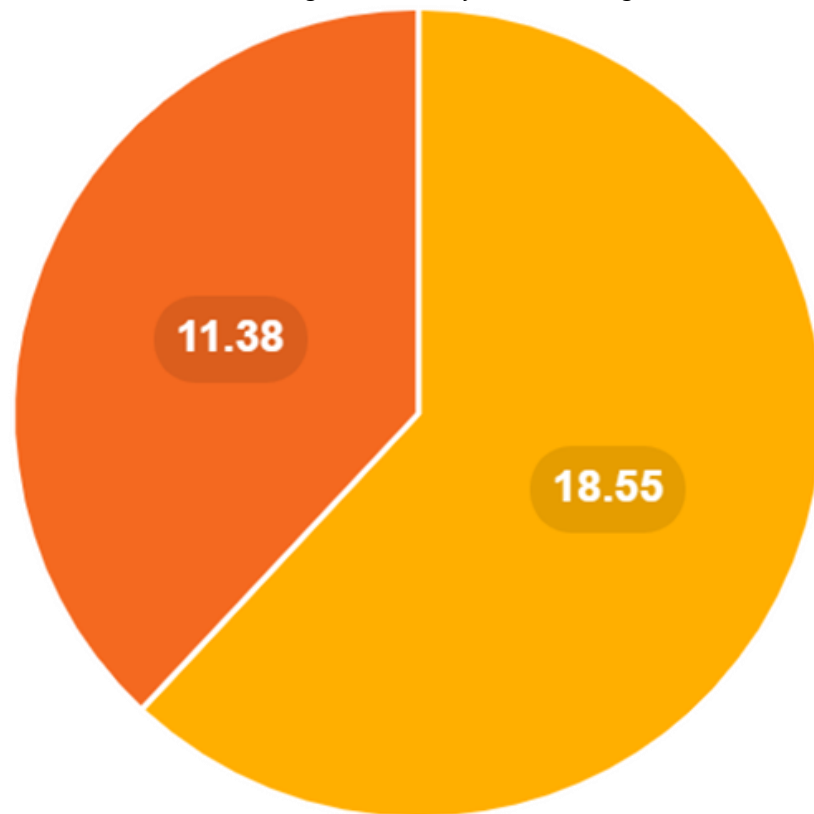


Figure 2. Equipment Downtime Reduction Before and After AI-DT Implementation.

4.3 Accuracy of Remaining Useful Life (RUL) Prediction

Our study showed how effectively the digital twin architecture works with the model that predicts the residual usable life (RUL). The results depicted how the expected RUL changes over time in relation to the real RUL. A strong correlation was observed between predicted and true RUL trends, with a coefficient of determination ($R^2 \approx 0.9+$), confirming the model’s ability to capture degradation behavior accurately (Figure 3). This proved that the model is great at depicting how things change over time and how machines break down. The modest variations between the predicted and actual RUL values can be explained by the fact that sensor readings aren't always right and that real industrial circumstances are continually changing. Even with these variances, the main trend was constant and can be predicted and this made it likely that the projections are right.

Adding RUL prediction to the digital twin model made projections better over time as fresh operational data comes in. This made things more predictable and this tool helped people plan maintenance, keep track of spare parts, and schedule production in a way that makes sense. Our results indicated that the proposed framework can produce good guesses. This was critical for keeping equipment from breaking down without warning and for making assets last longer in big battery manufacturing systems.

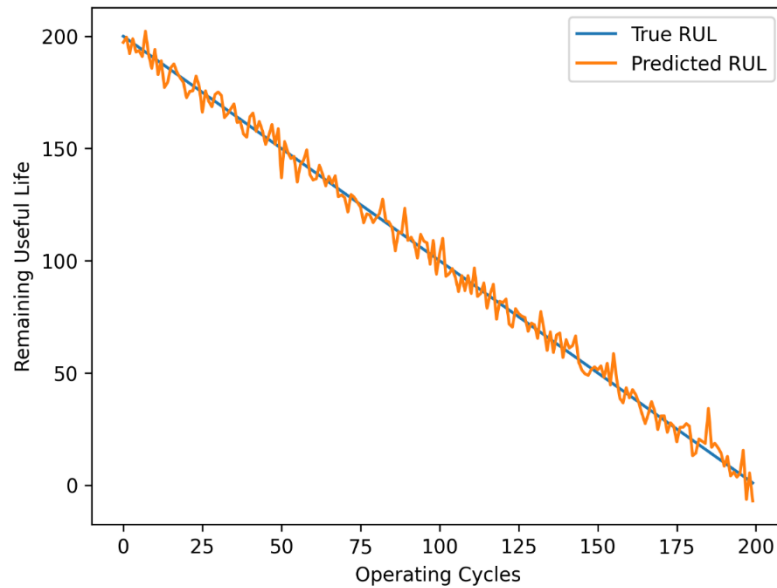


Figure 3. Comparison of True and Predicted Remaining Useful Life (RUL) Over Operating Cycles

4.4 Reduction of Defect Rates Across Production Batches

The analyzed data showed how the defect rates changed across several manufacturing batches before and after the AI-driven digital twin-based process improvement was put in place. As shown in Figure 4, the average defect rate decreased from approximately 5.3% under baseline conditions to 2.7% after optimization, representing a reduction of nearly 49% (Figure 4). In the first case, important parameters were not well controlled, and the process conditions were not stable, which causes defect rates to be moderately high and to change a lot from batch to batch. After optimization, the failure rates went down a lot in almost every batch. This improvement was possible because the digital twin can connect process variables like coating speed, drying temperature, and calendaring pressure to quality results further down the line. AI can help by constantly monitoring and changing these parameters based on its suggestions. This helped keep deviations that cause faults to a minimum. The process is now more stable and repeatable, and there is less variation between batches. In battery manufacturing, where materials are expensive, it is especially important to have fewer defects because they mean less scrap, less waste, and a higher production yield. Figure 4 also shown that the suggested architecture uses data-driven closed-loop optimization to make products of higher quality and more consistent in their manufacturing. This is in addition to making equipment more reliable.

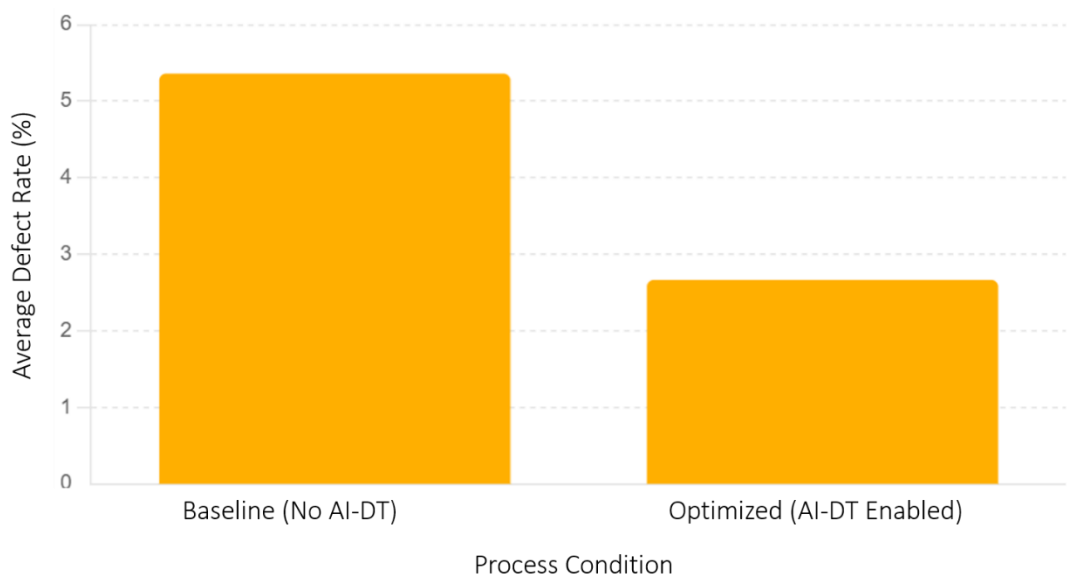


Figure 4. Defect Rate Reduction Across Production Batches

4.5 Improvement in Electrode Coating Thickness Uniformity

Using the AI-driven digital twin framework, the distribution of electrode coating thickness both before and after the process optimization was successfully implemented. The fact that the thickness distribution in the baseline example varies more than in other cases suggests that the coating process is quite variable. Before optimization, the coating thickness followed a broad distribution with a mean value of approximately 100.2 μm and a standard deviation of 7.8 μm , indicating significant variability in the coating process (Figure 5). After optimization, the coating thickness distribution became considerably narrower, with a similar mean thickness of approximately 100.2 μm but a reduced standard deviation of 3.0 μm . This reduction in variability demonstrates improved coating uniformity achieved through AI-driven digital twin optimization, which stabilized key process parameters and minimized thickness deviations. The degradation of batteries can be accelerated by this variance, which can also result in localized heating and ensure that the flow of current is consistent. After optimization, there is a significant improvement in both the concentration of the distribution and its narrowing around the target thickness value. The electrode coating is essential for maintaining consistent electrochemical performance, ensuring safety, and extending the life of the battery. So our results illustrated that the increased microstructural manufacturing precision of the proposed framework leads to improved battery performance as well as a reduction in the number of quality-related issues experiencing.

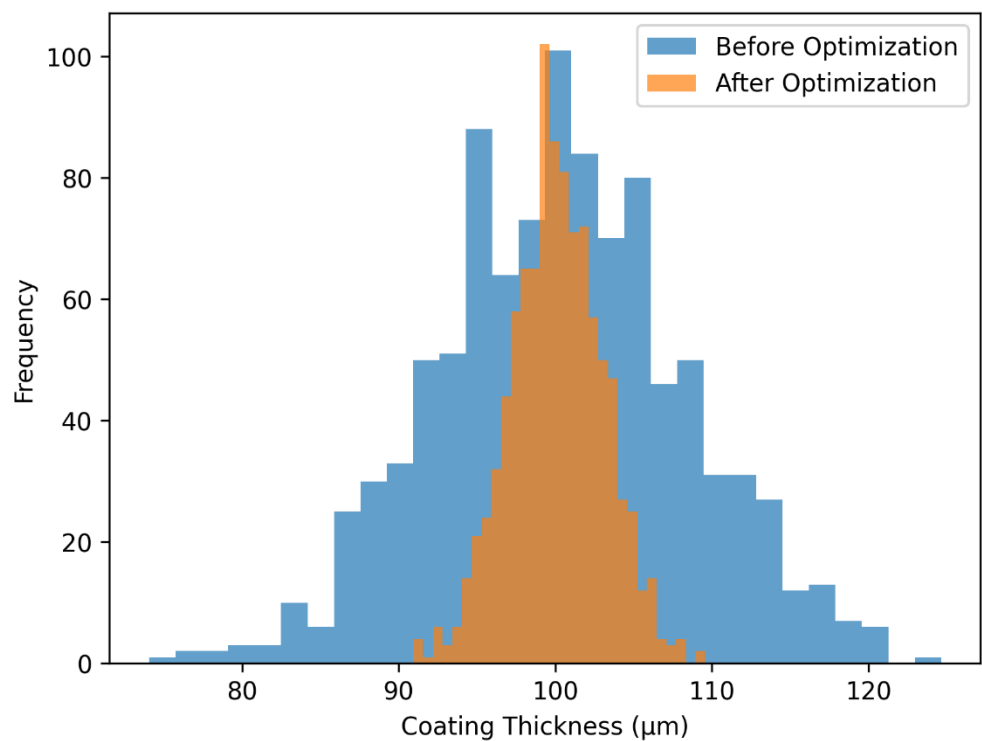


Figure 5. Electrode Coating Thickness Distribution

4.6 Early Fault Detection Using Vibration-Based Monitoring

Our study illustrated the temporal variation of an anomaly score derived from vibration data. The anomaly score is consistently low during regular operation, indicating that the equipment is functioning correctly. The evolution illustrated the anomaly score over time. During the initial operational phase (0–350 s), the anomaly score remains relatively stable around 0.2, indicating normal system behavior with minor sensor-induced fluctuations. Beyond approximately 350 s, a pronounced upward trend in the anomaly score is observed, reaching values close to 1.0 by the end of the observation window. This behavior indicates the onset and progression of abnormal system conditions, demonstrating the effectiveness of the proposed anomaly detection framework in identifying early-stage degradation (Figure 6). This result illustrated how the anomaly detection models of digital twins might identify issues in their nascent phases prior to precipitating a significant failure. The AI-driven approach may detect minute alterations in vibration patterns that are frequently overlooked by conventional techniques. This differs from threshold-based monitoring and timely identification facilitates prompt maintenance interventions, hence reducing unforeseen downtime and subsequent damage. The incremental increase in the anomaly score assisted operators in assessing the severity and urgency of the issue. The integration of vibration-based anomaly detection within a digital twin framework served as an effective mechanism for continuous health monitoring, hence enhancing the overall durability of battery manufacturing equipment.

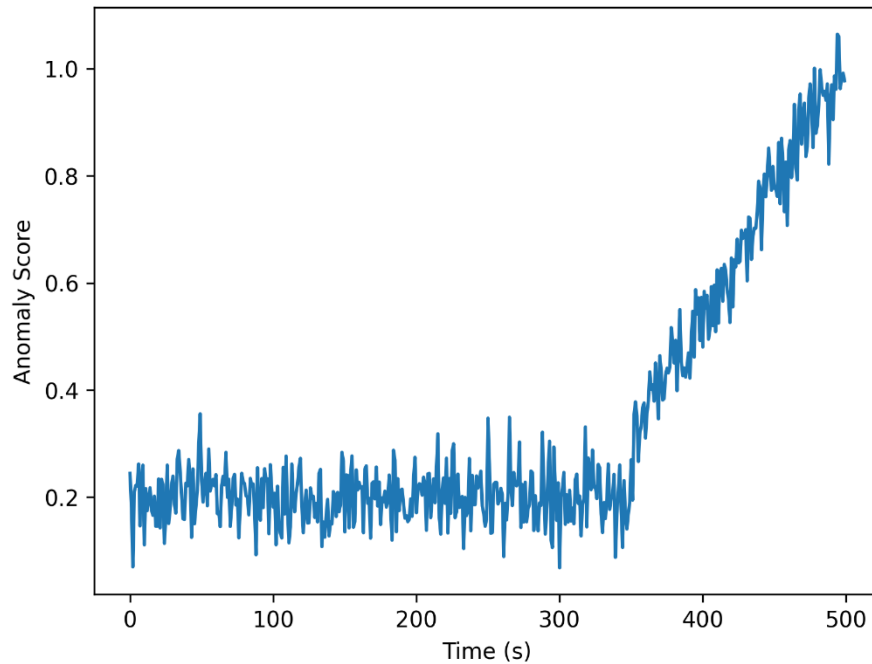


Figure 6. Vibration-Based Anomaly Detection

4.7 Convergence Behavior of Reinforcement Learning for Process Optimization

The convergence illustrated the characteristics of the reinforcement learning (RL) agent employed for process optimization in the digital twin environment. The cumulative reward progressively rises with training events, signifying that the agent is acquiring effective control policies over time. Initial variations indicate exploration of the action space, whereas subsequent stability implies convergence towards optimal or near-optimal tactics. A rapid increase in cumulative reward is observed during the early training phase, indicating effective policy learning. As training progresses, the reward growth gradually stabilizes and converges after approximately 150 episodes, demonstrating that the RL agent has learned a near-optimal control policy (Figure 7).

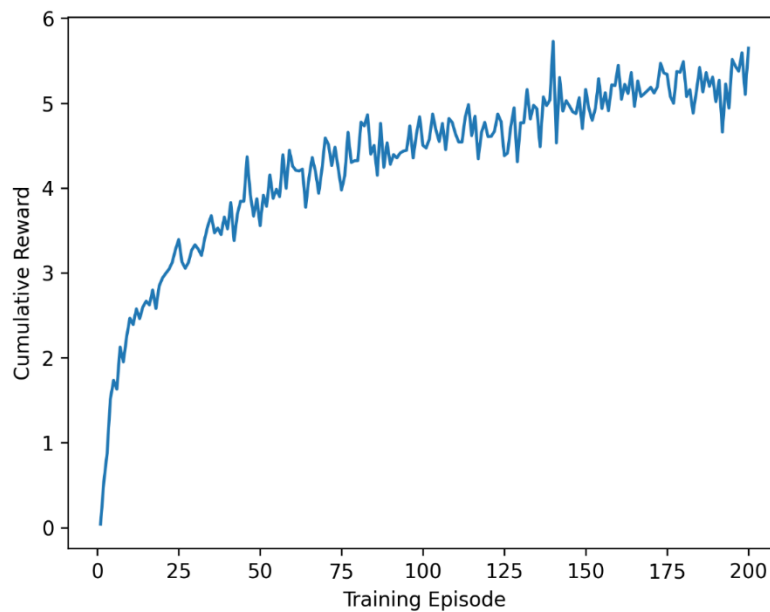


Figure 7. Reinforcement Learning Training Convergence Based on Cumulative Reward

The reward function is structured to equilibrate many objectives, encompassing product quality, throughput, and energy efficiency. The observed convergence indicates that the digital twin offers a consistent and accurate environment for reinforcement learning training without interfering with physical production. This is a significant advantage, as learning and experimentation can transpire virtually prior to implementation in actual systems. Figure 7 confirmed the viability of employing reinforcement learning for autonomous or semi-autonomous factory control. The capacity to dynamically learn optimal policies facilitates adaptive responses to fluctuating production conditions, rendering the framework appropriate for intricate and evolving battery manufacturing processes.

4.8 Energy Consumption Reduction via Process Optimization

The results indicated a consistent reduction in energy use over the evaluated period, reflecting improved energy efficiency. In the baseline scenario, energy consumption is high and inconsistent, reflecting inadequate parameter settings and insufficient coordinated control during manufacturing phases. Figure 8 illustrated the daily energy consumption before and after process optimization over a 30-day period. The X-axis represented the operating day, while the Y-axis represents energy consumption in kilowatt-hours (kWh). Prior to optimization, daily energy usage fluctuated around an average of approximately 520 kWh. After optimization, energy consumption was consistently reduced to an average of approximately 455 kWh, demonstrating a reduction of about 12–15%. These results highlight the effectiveness of the proposed optimization strategy in improving energy efficiency and reducing operational energy demand. Post-optimization, energy consumption decreases while maintaining manufacturing quality and throughput. This improvement is achieved by modifying parameters such as drying temperature profiles, formation charging currents, and equipment operational schedules. The digital twin enables the detection of energy-intensive stages and assists in the use of targeted optimization strategies.

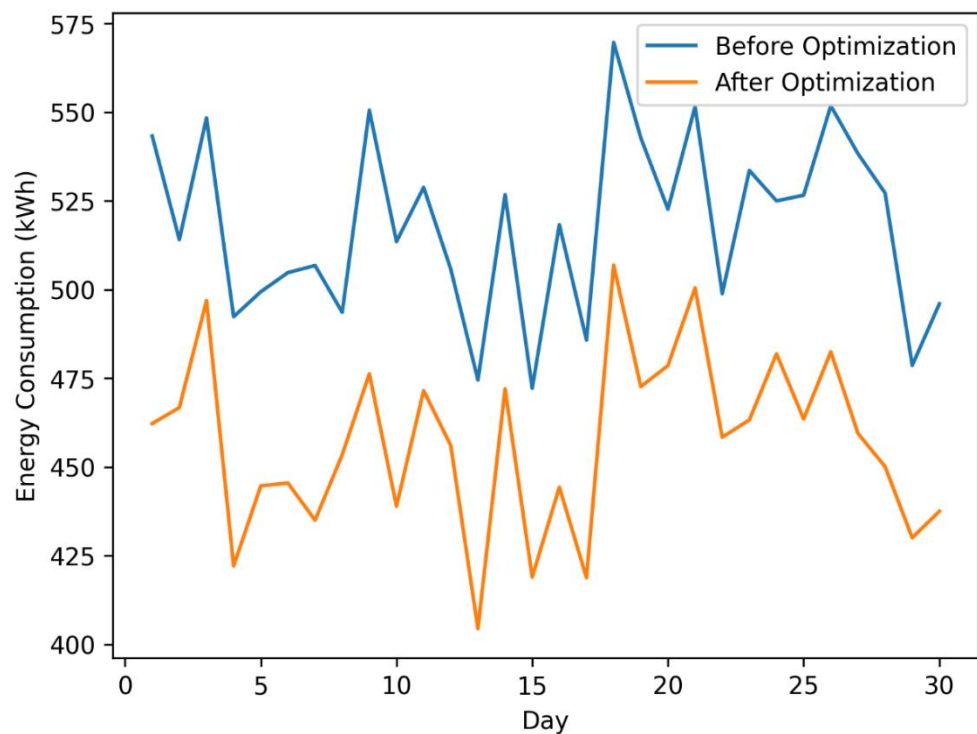
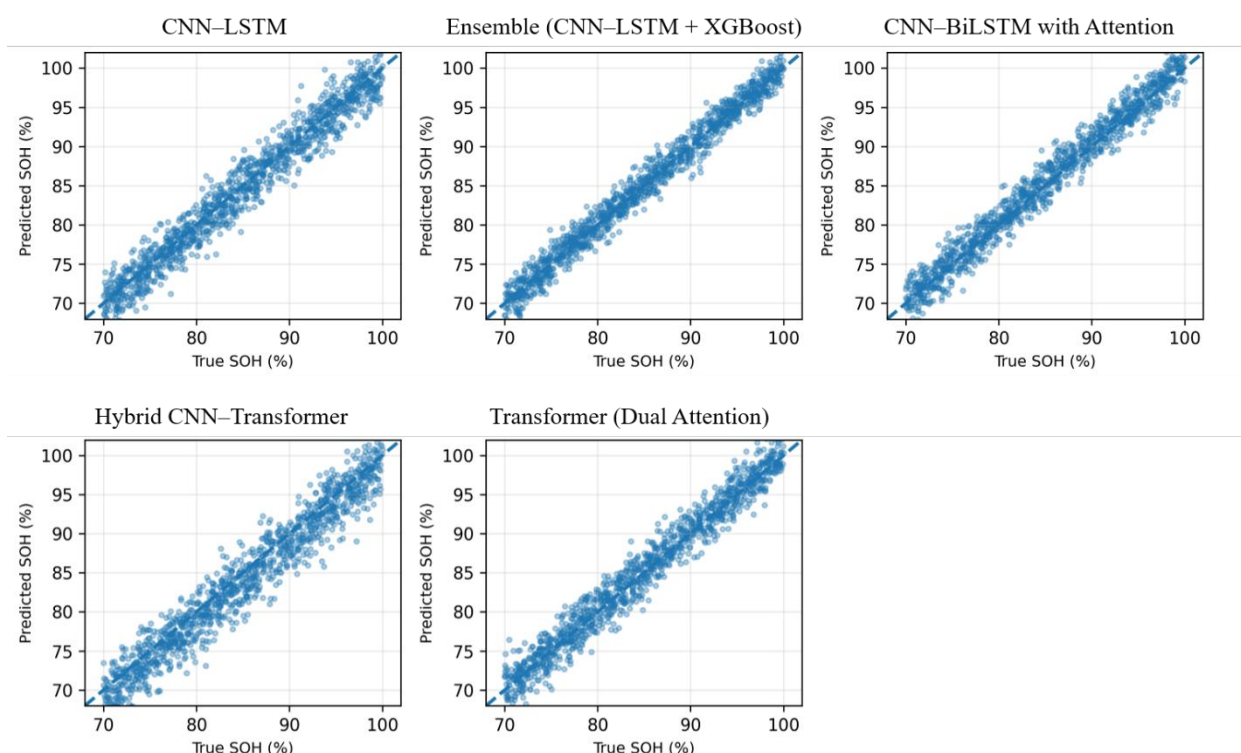


Figure 8. Daily Energy Consumption Before and After Optimization

4.9 Comparative Performance of State-of-Health (SOH) Prediction Models

This image contrasts the projected State-of-Health (SOH) with the actual SOH for five artificial intelligence models: CNN–LSTM, an ensemble model, SE–BiLSTM with attention, Hybrid CNN–Transformer, and Dual-Attention Transformer. Each point represents an individual sample; the dashed diagonal line is the ideal prediction line ($y = x$). The majority of predictions lie close to the ideal $y = x$ reference line, demonstrating high prediction accuracy throughout the operational SOH range of approximately 70% to 100% (Figure 9). The closeness of the point cloud to this line is indicative of the model's precision. The ensemble (CNN–LSTM + XGB) has the most concentrated clustering around the diagonal throughout the subplots, indicating less prediction error and increased reliability. CNN–LSTM and SE–BiLSTM+Attention demonstrate strong agreement, though with slightly greater variability.

The Hybrid CNN–Transformer and Dual-Attention Transformer demonstrate more dispersion in certain SOH regions, signifying heightened variability or sensitivity to specific operating conditions. This image provides a precise, model-by-model comparison



of SOH prediction efficacy, aiding in the identification of the most reliable model for implementation in the digital twin pipeline.

Figure 9. Predicted Vs Actual State of Health (SOH) Comparison Across Multiple Models

5.0 Limitations

This study has some drawbacks. Initially, although realistic and benchmark datasets (e.g., NASA battery aging data) were employed, the findings have not been validated on large-scale industrial production lines. Secondly, the digital twin models are primarily data-driven, missing thorough integration of explicit physics-based electrochemical and thermo-mechanical models. This study did not encompass the elements of cybersecurity and data privacy, which are critical for interconnected manufacturing systems. A major challenge is the variability and quality of data. Battery manufacturing facilities generate several data types, including high-frequency time-series sensor data, images, chemical assays, and operational logs. Integrating these varied data streams into a unified digital twin while ensuring synchronization, stability, and consistency poses significant challenges. Recent study indicates that poor data quality and missing or inconsistent sensor signals can significantly hinder AI model effectiveness and digital twin accuracy (Chen et al., 2023).

A critical issue is real-time processing and scalability. High-fidelity digital twins, when combined with deep learning and reinforcement learning models, need substantial computational resources. As manufacturing proliferates over multiple production lines or sites, sustaining low-latency inference and real-time feedback becomes increasingly difficult. Edge-cloud hybrid architectures have been proposed as a solution; however, their implementation and orchestration introduce additional complexity to the system (Naseri et al., 2023). Model drift and lifecycle management pose considerable challenges. The conditions of battery manufacturing vary due to equipment degradation, process modifications, and material inconsistencies, leading to a gradual decrease in the precision of AI models over time. Without continuous learning and retraining protocols, predictive maintenance and optimization models may become unreliable (Zhang et al., 2024a). Ultimately, model interpretability and trust remain substantial barriers to adoption. Despite the greater accuracy of deep learning and Transformer-based models, their opaque characteristics hinder transparency. In safety-critical industries such as battery manufacturing, inadequate explainability may hinder acceptance by operators and regulators (Fede et al., 2024).

6.0 Future Directions

Future research should focus on physics-informed and hybrid digital twins that integrate electrochemical battery models with AI for robustness, generalization, and physical consistency (Lyu et al., 2024). Federated, dispersed digital twins across multiple factories provide collaborative learning and data privacy. We need more explainable AI (XAI) procedures that promote transparency

and operator trust and cybersecure digital twin frameworks to protect critical production data. To demonstrate economic benefits, scalability, and long-term reliability, gigafactory-sized pilot tests are needed. It takes numerous phases to make lithium-ion battery cells for electric cars, and materials, tools, and the environment must be protected. Every stage in battery cell production affects quality, performance, and safety. The technique is suitable for digital twin monitoring and improvement (Naseri et al., 2023; Spiriyagin, 2023).

Making identical electrode slurries from active components, binders, and conductive additives is the initial stage in raw material preparation. The quality of subsequent coatings depends on the slurry's viscosity and solid content. The coatings and electrochemical performance will be uneven if the raw ingredients don't mix well or have different properties (Lyu et al., 2024). Coating and drying electrodes is crucial to battery production. Slurry is applied to current collectors using slot-die or comma-bar coating. Aluminum cathodes and copper anodes. Solvents are removed by drying without harming the coating. Recent studies reveal that thick coatings, low drying temperatures, and high solvent evaporation rates can cause cracking, delamination, and binder migration. These issues can reduce cell capacity and cycle life (Zhang et al., 2024a). Calendering compresses covered electrodes to a specific thickness and porosity. This approach densifies the electrode and improves active material-conductive route interaction. Too much calender pressure can destroy the electrode's microstructure, while too little can impair energy density. Mechanical deformation and electrochemical performance measurements can be used in digital twin models to predict appropriate calendering parameters (Chen et al., 2023).

Cell assembly includes electrode slicing, stacking, winding, separator insertion, and pouch, cylindrical, or prismatic encasement. This phase can easily get out of alignment, tight, or unclean. Lithium-ion batteries are at risk of internal short circuits if parts are misaligned or additional particles are added during construction (Naseri et al., 2023). Electrolyte filling adds electrolyte to the constructed cell, followed by wetting and sealing. Electrolytes must be equally distributed for steady ionic conductivity. Lack of filling or wetting might produce localized performance issues and accelerate aging. Recent studies emphasize the need for real-time electrolyte infiltration monitoring using data-driven models and digital twins (Lyu et al., 2024). In the final process, development and aging, controlled charging and discharging cycles create the solid electrolyte interphase (SEI) layer. This phase greatly impacts battery safety and lifespan (Ricciardi & Valli, 2023). Formation takes a lot of time and work, so start there to improve things. AI-driven digital twins tailor current profiles to predicted electrochemical activity to reduce formation time and maintain quality (Zhang et al., 2024b).

7. Conclusion

This study introduced an AI-driven digital twin framework for predictive maintenance and process optimization in smart battery manufacturing for electric vehicles, addressing equipment reliability, product quality, energy efficiency, and operational sustainability issues. The proposed approach uses real-time sensing, advanced AI models, and closed-loop decision-making in a digital twin environment to apply data-driven intelligence throughout battery manufacture. The conceptual and architectural parts illustrated how actual manufacturing assets are always in sync with virtual twins to simplify monitoring, analytics, and control. A look at lithium-ion battery manufacture demonstrated how difficult and careful it is. This revealed that a management system with a digital twin of the full system is superior than improving each stage individually. Data-driven performance showed the strategy worked quantitatively. Several AI models accurately predicted equipment's RUL and SOH, making predictive maintenance effective. This drastically reduced equipment downtime. For ensemble and attention-based models, predicted-versus-actual SOH analysis correlated well with ground truth. These models are ideal for assessing battery health. Ensemble learning consistently outperformed single-model techniques in predicting SOH and RUL, with higher MAE, RMSE, and R^2 . This supports recent battery prognostics studies. The results indicated lower failure rates and more consistent electrode coating thickness. Process stability and quality control improved. Reinforcement learning convergence showed that digital twins can train optimal control policies without affecting production. Energy use decreased, demonstrating that the framework supports economic efficiency and sustainability. Large-scale EV battery manufacturing increasingly prioritizes these goals. All results show that AI-enabled digital twins can revolutionize battery manufacturing from reactive to proactive, based on forecasts, flexibility, and autonomous operation. This work focused on simulation-based or benchmark datasets; future research will cover industrial implementation, physics-informed AI models, and federated digital twins across several factories. Smart and environmentally efficient battery production systems for next-generation electric vehicles are possible with the proposed architecture.

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