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Linking Process Parameters to Performance Outcomes: A Review of Predictive Frameworks in Cylindrical EV Battery Manufacturing

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Abstract: The performance of electric vehicles depends on lithium-ion battery manufacturing. Current manufacturing lacks standardized frameworks linking process parameters with field performance. This review examines 20 studies applying machine learning (ML) and deep learning (DL) to enhance quality control, defect prediction, and process optimization in battery production. Models like random forests, gradient boosting, and hybrid physics-ML systems are explored. This paper highlights gaps in model generalizability, interpretability, and scalability for intelligent battery manufacturing. Our first paper addressed supply chain quality; the second examined supply chain data gaps. This study focuses on correlating process parameters with product performance using ML and DL methods.

Keywords: Lithium-ion battery manufacturing, Process-performance correlation, Machine learning optimization.

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INTRODUCTION

The global push for carbon neutrality has accelerated EV adoption, increasing demand for lithium-ion batteries (LIBs) with improved performance and reliability. LIB manufacturing involves complex processes like slurry mixing, coating, drying, calendaring, and formation. Each stage's parameters directly impact cell quality and yield. Despite advances, a standardized method to correlate process parameters with cell-level Critical to Quality (CTQ) metrics remains absent, limiting predictive quality control. ML and DL approaches offer promise in modeling these relationships, yet many applications lack end-to-end integration.

OBJECTIVES OF THE STUDY

This research examines machine learning applications in lithium-ion battery production and frameworks connecting process parameters to performance metrics. It evaluates how data-driven techniques enable quality assurance in automated battery production. Through reviewing twenty papers, it examines relevance and future directions for building optimization frameworks in EV battery production. The study aims to address the following research questions:

- What machine learning models have been applied in lithium-ion battery manufacturing for quality control and defect prediction, and how effective are they in identifying anomalies during production?
- How do machine learning approaches model the relationship between manufacturing process parameters and battery performance metrics, and what techniques have proven most effective?
- How can insights from current machine learning applications be synthesized into a structured framework for modeling process-product relationships in battery manufacturing?

Problem Statement: Despite advancements in EV battery manufacturing, it remains unclear whether a standardized framework exists to correlate manufacturing process parameters with critical-to-quality (CTQ) metrics at the cell level. This gap complicates efforts to develop predictive functions ($y = f(x)$) for analyzing the impact of process variations on key performance indicators. By reviewing existing literature, this study aims to assess the presence of such frameworks, identify limitations, and highlight opportunities for improving predictive quality and process optimization in cylindrical EV battery production.

MATERIALS AND METHODS

This review consolidates literature on ML and DL in optimizing process parameters and quality control for cylindrical lithium-ion batteries, aiming to determine practical alignment of theoretical models and identify systematic predictive manufacturing blueprints. Steps in

Figure 1 were: identification, screening, assessment, and inclusion.

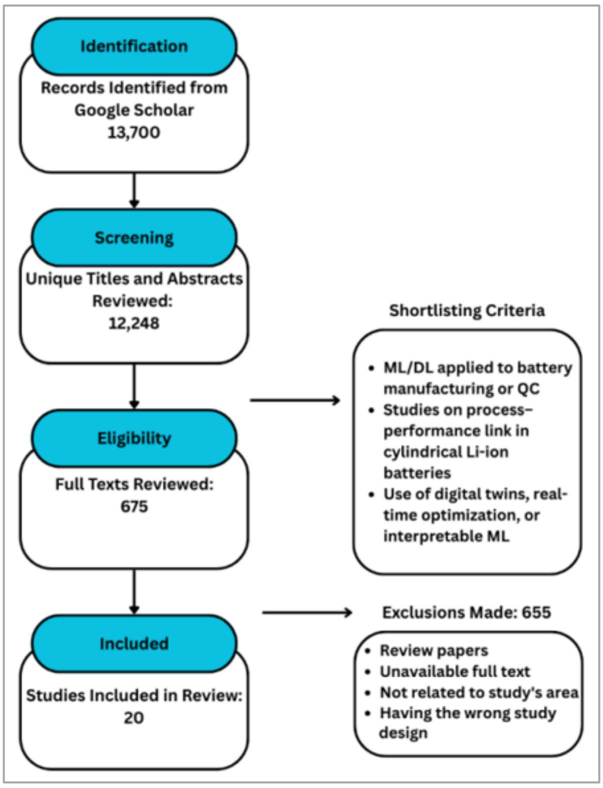

Fig. 1. Review Methodology

REVIEW METHOD

The review covered literature published post-2020, with some foundational earlier works, using IEEE, MDPI, ScienceDirect, SpringerLink, and Google Scholar. Search terms included ML/DL in battery manufacturing, quality control, parameter optimization, and digital twins.

Inclusion Criteria

1. **Works describing** ML/DL application in manufacturing processes and quality control of battery cells.
2. Research on process parameters and product performance in cylindrical lithium-ion batteries.
3. Contributions analyzing digital manufacturing tools like digital twins and real-time simulation optimization.
4. Empirical research on CTQ-benchmarked quality evaluation or interpretable ML-based frameworks.

Exclusion Criteria

1. Non-empirical works without practical implementation description.
2. Studies not relating to lithium-ion and EV battery cell production.
3. Publications not written in English.
4. Research on post-manufacturing diagnostic analyses.

Quality Assessment: Peer-reviewed articles were considered for empirical testing relevance to intelligent battery manufacturing, evaluated for methodological adequacy, research relevance, and industrial practice congruence.

LITERATURE SURVEY

What machine learning models have been applied in lithium-ion battery manufacturing for quality control and defect prediction, and how effective are they in identifying anomalies during production?

Figure 2 shows lithium-ion battery manufacturing quality control with ML for defect detection. The workflow classifies cells using ML models based on cycle life metrics, purging lower-quality cells to reduce waste. The system enables real-time parameter adjustments and anomaly detection for early corrections, demonstrating quality control's transformation through ML.

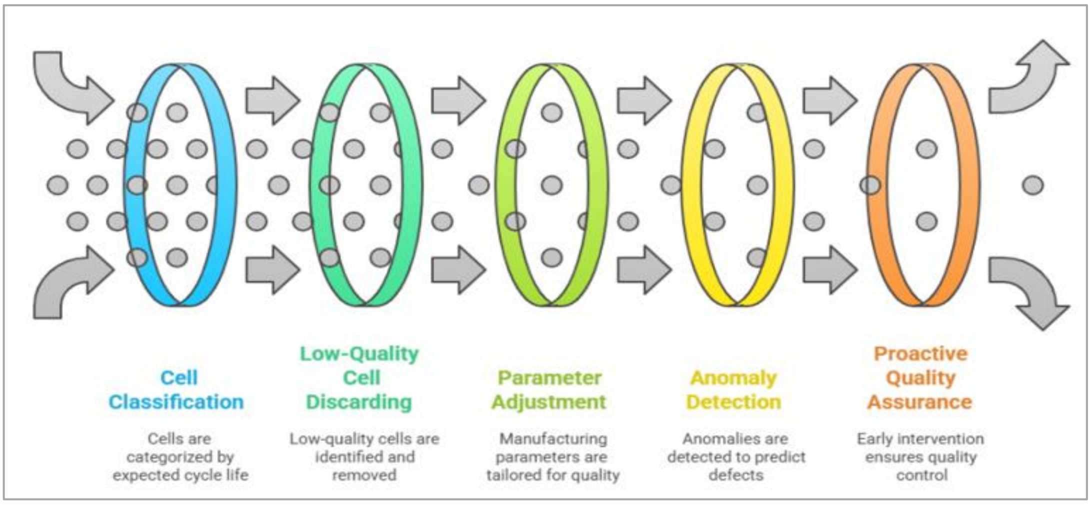

Fig. 2. ML-based quality control process in lithium-ion battery manufacturing.

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Survey of Data-Driven Models Used in Battery Manufacturing for Quality Control

Data-driven models advance lithium-ion battery quality **control**. Battery cells can be classified by expected cycle life using early-cycle data via random forests and gradient boosting [1]. Regression models analyze cathode **manufacturing parameters** and quality **factors** [2]. Machine learning techniques offer varying accuracy for anomaly detection and degradation prediction [3]. **Mapping** studies show ML applications in production [4]. Data-driven estimators **enable** real-time state estimation and fault detection [5].

Real-World Case Studies of Defect Prediction Systems in Battery Production

Advanced predictive models identify safety concerns through ML analysis of cycling data and environments. Systems detect resistance, voltage, or temperature risks for proactive measures [6]. Supervised learning analyzes EV battery data to identify health issues [7]. Combining empirical and physics-based data enhances anomaly detection [8]. State monitoring enables defect detection during production, transforming quality control [9].

How do machine learning approaches model the relationship between manufacturing process parameters and battery performance metrics, and what techniques have proven most effective?

Figure 3 shows ML's role in linking manufacturing parameters to battery **performance**. ML algorithms estimate process effects on performance. Simulations incorporate physics-based degradation. Real-time monitoring enables production adjustments balancing cost and quality.

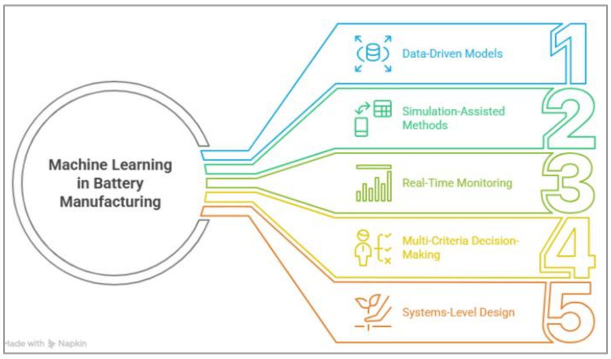

Fig. 3. Key ML-based components for modeling process-performance relationships in battery manufacturing

Data-Driven Models for Correlating Manufacturing Parameters with Battery Performance

Understanding manufacturing-performance relationships is crucial for lithium-ion production. ML techniques estimate process metrics affecting porosity and thickness, determining energy density and cycle life [10]. Models examine coating ratio impacts on mass loading [11]. Electrochemical features integrate through simulations, linking degradation with particle connectivity [12]. Monte Carlo simulations assess parameter risks [13]. Digital platforms monitor cathode microstructure for dynamic adjustments [14].

Techniques for Effective Process-Performance Prediction in Battery Manufacturing

Combining simulations with ML optimizes lithium-ion manufacturing. Models forecast energy densities using synthetic data [15]. Material content and calendaring compression are key parameters. Gaussian Process Regression enables C-rate optimization [16]. Decision-making models balance cost, safety, and performance [17]. The Analytic Hierarchy Process enables trade-offs while systems design affects resistance and degradation [18].

How can insights from current machine learning applications be synthesized into a structured framework for modelling process-product relationships in battery manufacturing?

Figure 4 shows battery manufacturing optimization using ML and DL for intelligent frameworks. The process involves developing ML models relating performance to parameters, system integration, hybrid model implementation, and scalable optimization. This approach transitions to industrial-scale production.

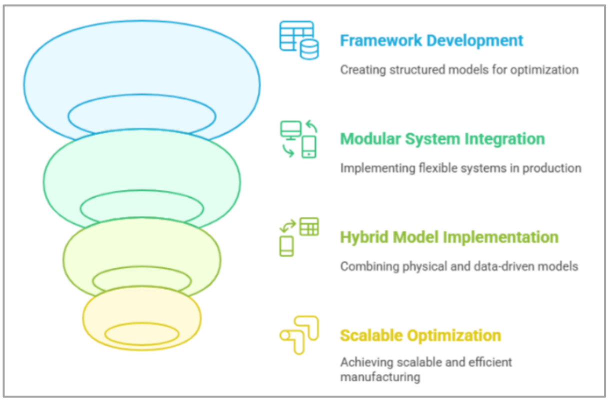

Fig. 4. A layered ML/DL framework for scalable optimization in battery manufacturing.

Building a Structured Framework for Process-Product Optimization Using ML/DL

Lithium-ion battery manufacturing models combine mechanistic and data-driven techniques. Digital tools with process simulation assess manufacturing parameters on performance. Formation process optimizes solid-electrolyte interphase through temperature parameters [20]. Digital platforms connect microstructural features with performance. Through simulation, architectures can be designed with minimal testing [14]. Data-driven models correlate process variables with performance [10].

Conceptual and Practical Frameworks for Scaling ML/DL Models in Battery Manufacturing

Scaling machine learning models requires structured systems for production settings. Machine learning supports material discovery and quality control but lacks

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standardization. Digital twins produce synthetic datasets for surrogate models [15]. Hybrid models incorporating physical principles enhance dependability. These frameworks integrate transfer learning and sensing to align signals with simulations for real-time control [8].

RESEARCH FINDINGS

Accuracy of Literature Predictions on Data-Driven Battery Manufacturing

Literature predicts machine learning application in lithium-ion battery manufacturing. Initial assessments highlighted needs for predictive quality control and performance optimization. Studies recognize machine learning as driving intelligent manufacturing and integrating process metrics.

"Machine learning is emerging as a transformative tool across the battery manufacturing pipeline, supporting predictive modelling and performance-oriented design."

Alignment with Risk-Informed and Process-Driven Modelling Approaches

Recent manufacturing models use Bayesian Optimization and Gaussian Process Regression for evaluating uncertainties in porosity and electrode thickness. Digital twins and surrogate models integrate processes with probabilistic learning.

"Stochastic and simulation-driven models are increasingly integrated into ML frameworks to address variability in manufacturing and its impact on performance."

Impact on Innovation and Process Efficiency

The implementation of real-time optimization tools and intelligent feedback mechanisms enables microstructure-level predictive control, improving efficiency and data-driven innovation.

"Predictive and feedback-driven frameworks have begun to transform manufacturing efficiency, offering a pathway to faster and more sustainable battery production."

Progress Toward Global and Scalable Frameworks

Literature synthesis shows increased development of globally deployable ML systems in battery production, with modular architectures and transferable practices enabling consistent deployment.

"Scalable ML systems require modular design, standard datasets, and interpretable outputs—principles that are increasingly being implemented in modern manufacturing workflows."

Anticipated Challenges and Criticisms

Challenges remain in standardization, data representation, expertise integration, and control feedback. Ethical concerns include explainability and data confidentiality. New approaches must integrate real-time responsiveness and domain standards.

"To achieve long-term impact, ML frameworks in battery production must evolve to include explainability, physical constraints, and dynamic learning capabilities."

POSSIBLE GAPS

Lack of Standardized Frameworks for Process-Product Modelling

Machine learning in lithium-ion battery manufacturing lacks harmonized models integrating process parameters and performance. Most studies focus on single processes without holistic frameworks. The absence of universal designs limits knowledge transfer across production settings.

"Current methodologies remain fragmented and are often limited to specific case studies, lacking the ability to scale across multiple manufacturing lines and chemistries."

Data Quality, Availability, and Uncertainty Handling

Limited quality production data hampers model training. Facilities often lack infrastructure to capture process data. Models don't account for uncertainties like thickness variability or slurry inhomogeneities. While stochastic models show potential, implementation remains challenging.

"Data variability in electrode properties and limited access to real-time process feedback restrict the reliability of current ML-based optimization pipelines."

Integration of Domain Knowledge and Physical Constraints

Most models treat manufacturing as black-box problems, overlooking domain knowledge. Few integrate mechanistic knowledge into model architecture. Incorporating physical laws into learning pipelines remains difficult.

"Few data-driven models integrate mechanistic insights or physical constraints, limiting their use for high-confidence production optimization."

Limited End-to-End Feedback Loops and Real-Time Control

Real-time process control using machine learning lags behind. Models operate statically without continuous sensor data updates, limiting self-governing systems.

"Real-time adaptation and closed-loop control remain missing in many proposed ML frameworks, reducing their effectiveness in high-throughput manufacturing environments."

CONCLUSION

Summary of Key Findings

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This review examines ML and DL applications in cylindrical lithium-ion battery manufacturing optimization. While ML integration expectations are visible, gaps persist. Risk-informed and hybrid physical-ML frameworks have progressed, but literature indicates fragmentation and lack of standardization affecting smart manufacturing systems.

Significance and Implications

These findings are crucial for systems engineering and data science professionals in battery production. The review shows the importance of ML with domain knowledge to improve accuracy and efficiency. As the battery industry faces EV market demands while maintaining quality, it provides recommendations for flexible management structures addressing systems control challenges.

LIMITATIONS

Models are created within fixed scenarios with limited extensibility, focusing on specific production stages rather than integrated solutions. The lack of uniform datasets and standards limits model utilization. Many ML methods remain unbound by physical system realities, making implementation difficult in safety-critical environments. These gaps show current solutions inadequately address manufacturing complexity.

Future Research Directions

Future work should develop modular structures incorporating mechanistic and simulation-informed ML approaches for battery manufacturing. Models need industrial validation for production variability. Research should explore feedback loops, digital twins, and edge computing for real-time control. Studying technology deployment in small enterprises will be crucial for widespread manufacturing intelligence adoption.

Final Thoughts

This review emphasizes the alignment of machine learning theory and manufacturing practice, while extending the need for interpretable frameworks. As EV battery production grows, there is demand for adaptive systems optimizing performance and safety. Industry and research communities must collaborate on solutions. Active review will ensure responsiveness to production challenges and technological changes.

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