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Review

Quality Control and Management Systems for Lithium-Ion Battery Production: A Systematic Literature Review

Christian Ploder*, Alessandro Allegro, Reinhard Bernsteiner

Department Management, Communication & IT, Management Center Innsbruck, Innsbruck, Austria
E-mail: Christian.Ploder@mci.edu

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Abstract: In response to increasing environmental concerns and the transition toward electromobility, lithium-ion batteries (LIBs) have become the dominant energy source for electric vehicles. However, their production remains costly and technically complex, with quality issues significantly contributing to high scrap rates and safety risks. Robust quality control and management practices are essential for performance and cost efficiency. This study conducts a systematic literature review (SLR) to identify and analyze quality-related methodologies applied in LIB manufacturing. Following the preferred reporting iems for systematic reviews and meta-analyses (PRISMA) framework, 46 peer-reviewed articles published between 2014 and 2024 were selected from four major databases. The results highlight the prevalence of data-driven techniques, especially machine learning, and emerging approaches like digital twins and computed tomography. This SLR contributes to improving quality assurance in battery production by synthesizing current best practices and identifying areas for future research.

***Keywords*:** lithium-ion battery production, quality control, quality management, systematic literature review, machine learning

1. Introduction

Among the main challenges that humanity has to face, it is possible to identify the diminishing availability of fossil fuels, coupled with their significant environmental impact. This is particularly relevant considering the transportation modes currently employed, which are still mainly carbon-based.

To push the development of innovative and more sustainable solutions, organizations such as the European Union are actively promoting emission-free mobility, with notable actions being put in place, including a ban on the production of fossil fuel-powered vehicles, starting in 2035. This represents a critical step toward environmentally neutral transportation. Among the alternatives, electric vehicles (EVs) have emerged as the leading competitor to traditional fossil fuel-powered cars. Conversely, other greenhouse gas-free technologies, such as hydrogen-powered vehicles, show less promising trends. For instance, according to the specialized platform Hydrogen Insight, global sales of hydrogen vehicles saw a severe decline of 36.4% in 2023, despite growing in regions like Europe and Japan [1].

Considering electric vehicles, despite notable growing trends in sales, with an apparent acceleration from 2021 onward, they still result far from being a dominant solution on the market; in particular, according to a report published

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by the international energy agency (IEA), in 2023 electric vehicles accounted for approximately 18% of total car sales, with fossil fuel-powered cars maintaining their dominance.

To advance electromobility, researchers emphasize the importance of enhancing the performance and reducing the costs of electric batteries, which are commonly identified as key cost and quality drivers for vehicles. However, producing such batteries entails a complex manufacturing process, characterized by interconnected tasks requiring high precision. Even minor inconsistencies during production can result in defects, significantly increasing manufacturing costs. Addressing these challenges requires adequate quality control and management strategies, and because of that, this is identified as a key research area within the broad field of electromobility.

To support innovation and implementation of practical solutions, this study presents a systematic literature review (SLR) to explore methodologies, tools, and approaches designed to improve quality within lithium-ion battery (LIB) manufacturing-the predominant battery type for electric vehicles. The SLR will undergo the main aspects of the study conducted, including a brief but meaningful theoretical background on LIBs and their production process, a chapter that will explain the methodology applied for the study and all the steps involved within the research, and the results obtained, to then conclude by assessing the limitations and the room for improvement of the study.

2. Background

Intending to provide a meaningful background on the topic of the study, this section offers an overview of the structure and the characteristics of LIBs, as well as the relative production process.

First of all, it needs to be clarified that each LIB is typically described as a “battery pack”, composed of several individual cells, depending on the type of battery and its goal, and by a battery management system (BMS), which is a component that ensures safety and efficiency when the battery is operating. LIB cells typically have four main components: anode, cathode, electrolyte, and separator. During the charge phase of the battery, lithium ions are released from the cathode and stored in the anode. On the contrary, when the battery goes through discharge, the ions move in the opposite direction, flowing from the anode to the cathode. To ensure that both processes run smoothly, the electrolyte, a typically liquid material, and a porous membrane, named separator, are placed between the two electrodes. In particular, considering the currently adopted models of LIBs, the electrolyte is typically a solution that contains lithium salts and an organic solvent. At the same time, the separator is specifically aimed at keeping the electrodes apart and avoiding short circuits [2]. Different materials and designs can be chosen for the overall system, influencing the characteristics of the batteries from many perspectives [3]. Overall, the structure and functionality of LIBs are defined by the interaction of their primary components-anode, cathode, electrolyte, and separator-and the electrochemical processes that enable energy storage and release.

Considering the production process required for LIBs, it can be concluded that the process is quite complex, and it includes several interconnected variables and quality metrics, with non-linear relationships that often result in unclear and difficult to predict. Apart from some minor variations related to the selected materials and to other aspects that depend on the choices of the manufacturer, it can be concluded that the process typically involves three main phases: electrode manufacturing, cell assembly, and cell finishing; in addition to that, each production stage includes several tasks [4].

Electrode manufacturing, the process’s first phase, involves anode and cathode production. First of all, active materials, conductive additives, solvents, and binders are combined to create a slurry, in an activity named “mixing” [4]. Followingly, the slurry is coated with metallic foils, which will act as current collectors, and then it goes through a drying phase in which the solvent evaporates [4]. Rotating rolls then compress the electrodes in a phase that is called calendering, and has the aim of ensuring correct contact and conductivity between active material particles and current collector [4-5]. To conclude the electrode manufacturing stage, the electrodes are slitted to compose smaller electrodes, which undergo another vacuum drying phase to ensure that eventual residuals of solvent and moisture are removed correctly, preventing side reactions and corrosion [4-5].

Cell assembly is the following stage of the process. In this part of the process, electrodes are assembled into cells; this can be done by stacking the components in layers, in the case of pouch-shaped cells, or by winding them together, in the case of cylindrical cells. Despite winding results being significantly quicker, a high degree of precision is required to align the foils [4]. The unit is placed into a casing once the electrodes and separator are assembled. Then the electrolyte is introduced into the cell through a high-precision needle, ensuring the solution's correct dosing [4]. Lastly, the cell casing is sealed to prevent leakage and contamination, and the cell is finally pressed through rotating rolls to ensure the correct distribution of the electrolyte [4].

To conclude the manufacturing process, the cells undergo several activities to activate them electrochemically, evaluate their quality and safety, and ensure that they meet the customers' requirements. First of all, the cells undergo a series of charge and discharge cycles, to be correctly activated and to ensure the correct formation of the solid electrolyte interface (SEI) layer on the anode [4]. In this phase, data such as the capacity and impedance of the cells is gathered to perform an initial evaluation and sorting of the cells based on their quality characteristics [4]. In the end, the cells undergo aging and end of line (EOL) tests, to evaluate quality metrics; this analysis is mainly focused on the capacity of the cells and the identification of defects, but it often includes also pulse tests, internal resistance, optical controls, open circuit voltage (OCV) tests and leakage tests, if they are relevant for the manufacturer. Such evaluations enable the gradation of the cells, ensuring that cells offering similar performance are grouped to be assembled into LIBs [4].

3. Methodology

This chapter goes through a detailed description of the methodological aspects of this study, reporting the elements that led to the choice of the research methodology, the key requirements of an SLR, and the activities that have been carried out.

As mentioned, the research aimed to identify solutions explored in quality management and quality control for LIBs production. To summarise the goal, the following research questions have been defined:

RQ 1: "What quality management and control methods are applied or proposed in the academic literature to enhance lithium-ion battery manufacturing performance and reduce defect rates?"

To support the primary research question, the following sub-questions were also considered:

• RQ 1.1: What types of quality control and quality management systems are currently used or proposed for different phases of LIB manufacturing?

• RQ 1.2: Which technologies (e.g., machine learning, digital twins, simulations) are most frequently discussed in the literature, and in what contexts?

• RQ 1.3: What challenges, limitations, and research gaps are identified regarding implementing these methods in industrial settings?

A SLR aims to offer a complete, comprehensive, replicable, and unbiased review of a chosen topic. Therefore, it has been identified as a proper approach to satisfy the research objectives. Additionally, it can be noticed that the research question already defines some of the boundaries for scoping the analysis, such as the timeframe and language of the papers considered. To ensure that the study respects the strict criteria required, the preferred reporting items for systematic reviews and meta-analyses (PRISMA) framework has been followed, and the following steps have been carried out:

• Formulation of research question, with context and objectives identified;

• Definition of the research strategy, which should include the selection of research databases, keywords, and inclusion and exclusion criteria;

• Search the literature using queries that contain the selected keywords and inclusion criteria in the chosen databases. More extensive studies can involve different experts in charge of doing a part of the review independently and then discussing and merging the results of their work.

• Screening and quality assessment of the papers analysed, through the use of proper tools, such as quality checklists or questionnaires to be conducted by the researcher;

• Extraction of data, in which the chosen articles are carefully read to extract the relevant information;

• Synthesis and interpretation of results, when the information is combined effectively and transparently, and reorganized for the researcher to be able to report the results of the studies involved in the analysis [6-7].

Strictly adhering to this framework ensures that the analysis of the literature performed in the study is unbiased and replicable, in order to obtain consistent results.

To do so, first of all, the research question reported previously was defined. The research strategy has been developed, including selected databases, keywords, and eligibility criteria. Tables 1 and 2 report the chosen research databases, the research strings employed, the results obtained, and a summary of the inclusion and exclusion criteria applied.

Table 1. Research databases selected, number of articles found, corresponding search string

Database source	N. of articles	Search string
ScienceDirect	383	Year (s): 2014-2024; title, abstract or author-specified keywords: "lithium ion battery production" or "lithium ion battery manufacturing"; article type: research articles
DOAJ	298	Title or abstract: "lithium batteries production" or "lithium batteries manufacturing"; year (s): 2014-2024
Scopus	623	Title-abs-key (lithium and batteries and production) and pubyear > 2013 and (limit-to (language , "english")) and (limit-to (exactkeyword, "battery production") or limit-to (exactkeyword, "battery manufacture") or limit-to (exactkeyword, "production process")) and (limit-to (doctype, "cp") or limit-to (doctype, "ar"))
IEEE Xplore	34	Title or abstract: "lithium batteries production" or "lithium batteries manufacturing"; year (s): 2014-2024

The selection process was guided by predefined inclusion and exclusion criteria (see Table 2). All search results were screened by title and abstract, followed by a full-text review. The initial screening excluded papers relevant to quality management or lithium-ion battery production. A single researcher conducted the screening and selection, ensuring consistency. The joanna briggs institute (JBI) critical appraisal tool for experimental and quasi-experimental studies was used to assess methodological rigor. Each paper was scored across multiple criteria, including study design, data collection, and outcome reliability. Only documents that passed this threshold were included in the final synthesis.

Table 2. Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Title, abstract, or keywords contain "lithium batteries production" or "lithium batteries manufacturing"	Title, abstract, or keywords do not contain "Lithium batteries production process" or "Lithium batteries manufacturing"
Title, abstract, or keywords contain "quality control" or "error detection" or "quality monitoring" or "machine learning" or "data driven"	Title, abstract, or keywords do not contain "quality control" or "error detection" or "quality monitoring" or "machine learning" or "data driven"
Research published between 01.01.2014 and 01.03.2024 Language of the study: English	Research published before 01.01.2014 or after 01.03.2024 Papers that are not written in English

Initially, the research keywords were chosen to keep a broad perspective on the topic, and then narrow it down with new and more specific criteria, as shown in Table 2. This process allowed for the initial identification of 1,338 papers, which were then narrowed down to 151 with the second stage of keyword selection. At this point, it was necessary to undergo all the remaining eligible studies, carefully assessing each document's abstract, keywords, and content, and determining whether it was relevant to the analysis. In the end, 46 papers were eligible for the final stage of the analysis: a quality assessment of the studies, which was conducted to ensure the reliability of the material selected for the review and, consequently, of the study's results. The quality assessment has been conducted using the checklist for experimental studies provided by JBI, an international organization that supports different research types. In the end, the assessment results demonstrated the high level of the databases selected, as all of them provide peer-reviewed papers; in fact, all the papers evaluated obtained a sufficient score for being included in the study.

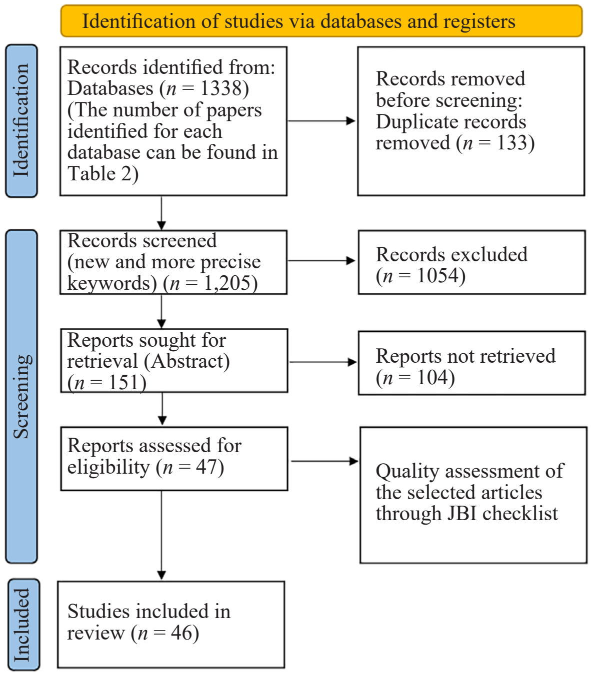

Figure 1. PRISMA diagram

The process strictly followed the PRISMA 2020 guidelines and involved the following sequential stages: identification, screening, eligibility, and inclusion. Each step was documented and is visually represented in the PRISMA flow diagram (see Figure 1), which summarizes the number of articles considered and excluded at each stage.

Table 3. Quality checklist of the articles selected for the review

Ref.	Authors	Title	Score
[8]	Cripps E, Pecht M	A Bayesian nonlinear random effects model for identification of defective batteries from lot samples	8
[9]	Leeb M, Wiegmann E, Kwade A, Daub R	A conceptual framework for data-driven optimization in the semi-dry electrode production for lithium-ion batteries	9
[10]	Haghi S, Töpper H-C, Günter FJ, Reinhart G	A Conceptual framework towards data-driven models in electrode production of lithium-ion battery cells	8
[11]	Xiao Y, Deng S, Han F, Wang X, Zhang Z, Peng K	A model-data-fusion pole piece thickness prediction method with multisensor fusion for lithium battery rolling machine	9
[12]	Kornas T, Knak E, Daub R, Bührer U, Lienemann C, Heimes H, et al.	A multivariate KPI-based method for quality assurance in lithium-ion-battery production	9
[13]	Wu Y, Saxena S, Xing Y, Wang Y, Li C, Yung WKC, et al.	Analysis of manufacturing-induced defects and structural deformations in lithium-ion batteries using computed tomography	7
[14]	Grabmann S, Harst F, Bernauer C, Weiss T, Zaeh MF	Analysis of photodiode signals for monitoring the laser beam welding process of cell-internal contacts in lithium-ion batteries	8
[15]	Anandavel S, Li W, Garg A, Gao L	Application of digital twins to the product lifecycle management of battery packs of electric vehicles	8
[16]	Kriegler J, Liu T, Hartl R, Hille L, Zaeh MF	Automated quality evaluation for laser cutting in lithium metal battery production using an instance segmentation convolutional neural network	9

Table 3. (cont.)

Ref.	Authors	Title	Score
[17]	Chen Y, Shu Y, Li X, Xiong C, Cao S, Wen X, et al.	Research on the detection algorithm of lithium battery surface defects based on embedded machine vision	8
[18]	Turetskyy A, Wessel J, Herrmann C, Thiede S	Battery production design using multi-output machine learning models	9
[19]	Schoo A, Moschner R, Hülsmann J, Kwade A	Coating defects of lithium-ion battery electrodes and their inline detection and tracking	8
[20]	Hoque MA, Nurmi P, Kumar A, Varjonen S, Song J, Pecht MG, et al.	Data-driven analysis of lithium-ion battery internal resistance towards reliable state of health prediction	8
[21]	Schnell J, Nentwich C, Endres F, Kollenda A, Distel F, Knoche T, et al.	Data mining in lithium-ion battery cell production	9
[22]	Turetskyy A, Wessel J, Herrmann C, Thiede S	Data-driven cyber-physical system for quality gates in lithium-ion battery cell manufacturing	9
[23]	Evans D, Luc P-M, Tebruegge C, Kowal J	Detection of manufacturing defects in lithium-ion batteries: analysis of the potential of computed tomography imaging	9
[24]	Zhang C, Silva GV, Abraham T, Herrmann C	Development of a virtual quality gate concept based on high-potential tests for lithium-ion battery cell manufacturing	9
[25]	Hwang Y-I, Park J, Munir N, Kim H-J, Song S-J, Kim K-B	Discrimination of poor electrode junctions within lithium-ion batteries by ultrasonic measurement and deep learning	8
[26]	Stock S, Pohlmann S, Günter FJ, Hille L, Hagemeister J, Reinhart G	Early quality classification and prediction of battery cycle life in production using machine learning	6
[27]	Haghi S, Keilhofer J, Schwarz N, He P, Daub R	Efficient analysis of interdependencies in electrode manufacturing through joint application of design of experiments and explainable machine learning	7
[28]	Yuan Y, Kong X, Hua J, Pan Y, Sun Y, Han X, et al.	Fast grading method based on data-driven capacity prediction for highly efficient lithium-ion battery manufacturing	8
[29]	Yao L, Xu S, Xiao Y, Hou J, Gong X, Fu Z, et al.	Fault identification of lithium-ion battery pack for electric vehicle based on GA optimized ELM neural network	8
[30]	Liu K, Li Y, Hu X, Lucu M, Widanage WD	Gaussian process regression with automatic relevance determination kernel for calendar aging prediction of lithium-ion batteries	8
[31]	Hoffmann L, Kasper M, Kahn M, Gramse G, Ventura Silva G, Herrmann C, et al.	High-potential test for quality control of separator defects in battery cell production	9
[32]	Fermín-Cueto P, McTurk E, Allerhand M, Medina-Lopez E, Anjos MF, Sylvester J, et al.	Identification and machine learning prediction of knee-point and knee-onset in capacity degradation curves of lithium-ion cells	8
[33]	Ank M, Stock S, Wassiliadis N, Burger T, Daub R, Lienkamp M	Influence analysis of production defects of lithium-ion cells using single-cell and multi-cell characterization	8
[34]	Stock S, Ceruti A, Günter FJ, Reinhart G	Introducing inline process and product analysis for the lean cell finalization in lithium-ion battery production	5
[35]	Niri MF, Liu K, Apachitei G, Ramirez LR, Lain M, Widanage D, et al.	Machine learning for optimised and clean Li-ion battery manufacturing: Revealing the dependency between electrode and cell characteristics	8
[36]	Tao R, Liang Z, Zhu S, Le Yang, Ma L, Song W, et al.	Mechanical analysis and strength checking of current collector failure in the winding process of lithium-ion batteries	9
[37]	Husseini K, Schmidgruber N, Henschel S, Mayer D, Fleischer J	Model-based optimization of web tension control for the flexible cell stack assembly of lithium-ion battery cells	8

Table 3. (cont.)

Ref.	Authors	Title	Score
[38]	Lu R, Li Y-C, Li Y, Jiang J, Ding Y	Multi-agent deep reinforcement learning based demand response for discrete manufacturing systems energy management	8
[39]	Kornas T, Wittmann D, Daub R, Meyer O, Weihs C, Thiede S, et al.	Multi-criteria optimization in the production of lithium-ion batteries	9
[40]	R-Smith NA-Z, Ragulskis M, Kasper M, Wagner S, Pumsleitner J, Zollo B, et al.	Multiplexed 16 × 16 li-ion cell measurements including internal resistance for quality inspection and classification	7
[41]	Schönemann M, Bockholt H, Thiede S, Kwade A, Herrmann C	Multiscale simulation approach for production systems	8
[42]	Karaki H, Thomitzek M, Obermann T, Herrmann C, Schröder D	Optimizing the microstructure and processing parameters for lithium-ion battery cathodes: a use case scenario with a digital manufacturing platform	7
[43]	Meiners J, Fröhlich A, Dröder K	Potential of a machine learning based cross-process control in lithium-ion battery production	9
[44]	Weng A, Mohtat P, Attia PM, Sulzer V, Lee S, Less G, et al.	Predicting the impact of formation protocols on battery lifetime immediately after manufacturing	6
[45]	Kollenda A, Husseini K, Henschel S, Schmidgruber N, Becker-Koch D, Braunwarth W, et al.	Quality assurance for flexible stack assembly of lithium-ion cells	8
[46]	Schnell J, Reinhart G	Quality management for battery production: a quality gate concept	9
[47]	Niri MF, Liu K, Apachitei G, Román-Ramírez LAA, Lain M, Widanage D, et al.	Quantifying key factors for optimised manufacturing of li-ion battery anode and cathode via artificial intelligence	7
[48]	Maddipatla S, Kong L, Pecht M	Safety analysis of lithium-ion cylindrical batteries using design and process failure mode and effect analysis	9
[49]	Haghi S, Summer A, Bauerschmidt P, Daub R	Tailored digitalization in electrode manufacturing: the backbone of smart lithium-ion battery cell production	7
[50]	Lenze G, Laue V, Krewer U	Time-efficient reparameterization and simulation of manufacturing impacts on performance of lithium-ion-batteries	8
[51]	Naumann A, Süß S, Mennenga M, Herrmann C	Towards an integrated control system for a scrap-free circular production of lithium-ion batteries	9
[52]	Wessel J, Schoo A, Kwade A, Herrmann C	Traceability in battery cell production	6
[53]	Wessel J, Turetskyy A, Wojahn O, Herrmann C, Thiede S	Tracking and tracing for data mining application in the lithium-ion battery production	8

The authors manually followed the selection and screening process, independently reviewing the titles, abstracts, and full texts of the 151 filtered studies. For the quality assessment phase, the standardized checklist provided by JBI for experimental and quasi-experimental studies was used. Each article was evaluated against key criteria such as clarity of research objectives, appropriateness of methodology, data reliability, and findings transparency. Only studies that met the threshold for methodological rigor were retained. Data from the final 46 studies (shown in Table 3) were extracted and organized in a structured Excel matrix, capturing elements such as study focus, methods applied, quality metrics discussed, and production phases addressed. The synthesis was performed by clustering similar methods and identifying dominant trends, innovations, and research gaps.

After completing all the steps, the studies identified were read, thoroughly synthesised, and reported, clearly indicating the research context, methodology applied, and results obtained.

4. Results of the research

The results of this study offer different perspectives and insights on several aspects of quality control and quality management for LIBs production, going from bibliometric considerations to identifying trends, dominant solutions, and research gaps in the field.

Considering the results of the bibliometric analysis conducted on the papers identified, some interesting aspects and trends can be identified. First of all, Figure 2 shows a growth in the number of published papers per year, with a peak reached in 2021; despite the analysis not being able to comprehend all the available material on the subject, as defined from the inclusion and exclusion criteria, this trend demonstrates the increase in interest in electromobility.

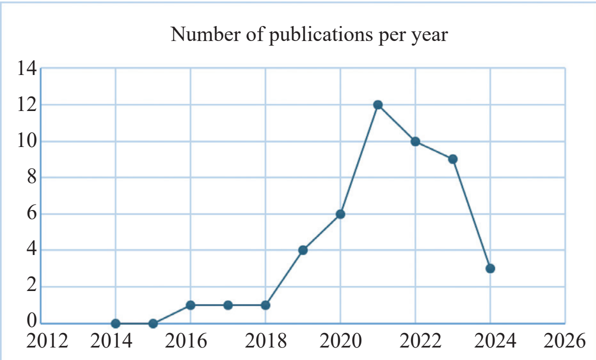

Figure 2. Number of articles involved in the review and distributed by year of publication

Additionally, the connections between the authors of the chosen studies are identified and shown in Figure 3. This can be relevant for identifying clusters of researchers and authors who were particularly influential in the field, and, eventually, even a possible opportunity for collaboration for future research. In the graph below, each dot represents an author with at least two publications involved in this analysis; the links connecting the authors identify the ones who worked jointly in at least one of the studies identified. Wider lines represent authors who cooperated in developing more publications, while larger dots indicate that the authors have several studies involved.

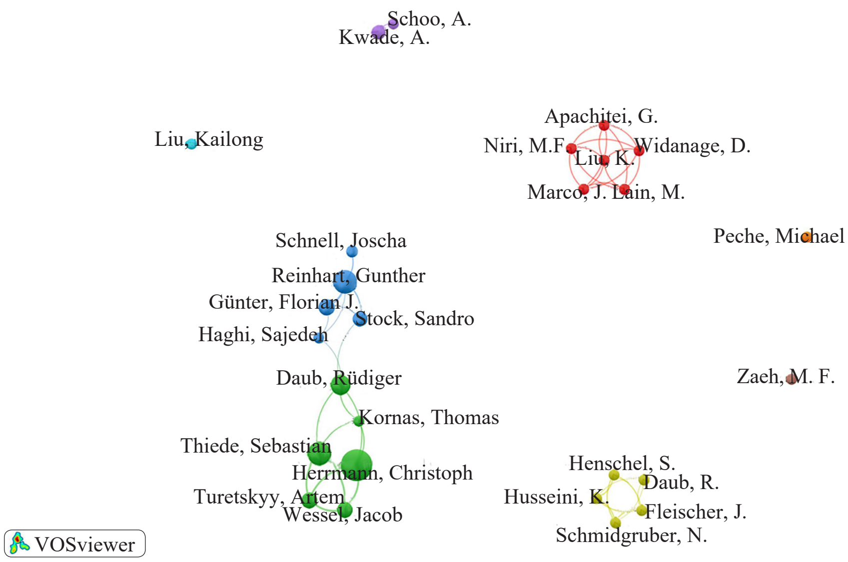

Figure 3. Diagram reporting the most involved researchers in the selected studies

Another analysis focused, instead, on the keywords of the papers identified, to detect connections (see Figure 4). In this case, each dot represents a keyword in at least two articles, while the lines connect keywords used together in at least one instance. The dot size represents the number of papers in which the reported keyword was declared, while the thickness of the lines identifies the number of articles in which both keywords are present.

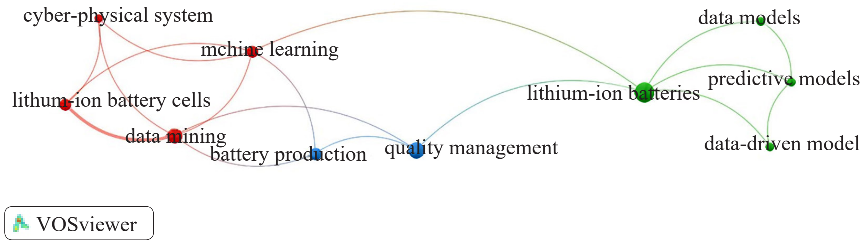

Figure 4. Diagram reporting the occurrence of research keywords

As previously mentioned, the analysis of the papers identified did not focus solely on bibliometric aspects; on the contrary, each study's objectives, methodology, and results were investigated. In the final part of this chapter, it is relevant to summarize the leading solutions and the key trends identified in the field.

To achieve this goal, the primary methodologies and techniques identified for each phase of the production process are hereby reported and commented. Considering electrode manufacturing, most of the approaches for quality control are based on data-driven and machine learning (ML) models. Different algorithms are evaluated among the available studies, and it is interesting to note that each model can vary in effectiveness for each task accompanying the electrode manufacturing phase. To mention some interesting cases identified, support vector machine and gaussian process regression (GPR) models result particularly effectively in the evaluation of the mixing task [17, 35, 54]. On the other hand, other studies that involve the application of ML to electrode manufacturing identify Gaussian regression, multiform coupling model, and convolutional neural networks (NN) as the most effective algorithms for quality control on calendering and slitting [9, 11, 16]. A different approach for the use of ML models is proposed by Chen et al., who applied Support Vector machine for the identification of the most influential parameters in electrode manufacturing; the results of the study identified mass loading, solid to liquid ratio and comma gap as key quality features in cell manufacturing, having a severe impact on the prediction of the overall quality level of the battery. Other methods identified include the implementation of computed tomography systems for coating error detection [23] and the analysis of pixel-wise pictures through an instance segmentation convolutional NN, for quality evaluations on the slitting task [16] However, such solutions reportedly require more experimentation. It is also important to mention the approach proposed by Lenze et al. [50], who developed a system for quick reparameterization and simulation to improve the electrode production process, focusing in particular on coating, calendering, and mass loading.

Going on with the LIBs manufacturing process, the primary methods identified for ensuring quality in the cell assembly phase involve using digital twins. This approach is beneficial because it allows testing the effectiveness of different process parameters without consuming materials and increasing production costs. Researchers identified a high degree of effectiveness of digital twins for evaluating web tension, a key product feature during the winding task [37, 45]. In addition, ML is a fundamental topic for cell assembly. In the study conducted by Grabmann et al. [14] ML models are applied using data gathered from photodiode signals to evaluate the quality level of packaging and welding, identifying possible abnormalities on the surface of the cells; a similar approach is adopted by Hwang et al., using ultrasonic signals for identifying poor welding on the cells [25, 55]. Zhang et al. [24] instead, they applied a system of virtual quality gates for controlling the separator layer of batches of LIBs; their solution has been tested at the Battery Lab Factory Braunschweig, and it showed promising results, enhancing process control and speeding up decision-making processes related to the quality of the separator.

Lastly, considering cell finishing, ML models are again identified among the most promising methods. Liu et al. [30] applied Gaussian process regression to predict the effect of different storage conditions on LIB cells. At the same time, Yuan et al. performed an early quality evaluation on LIB cells using a feed-forward NN and data gathered from wetting, formation, and cycling phases. Other methodologies identified deal principally with electrical tests [28]. In particular, the employment of a multiplexed measurement system for contemporary evaluation of the open circuit voltage and internal resistance of several cells, proposed by R-Smith et al., enables the reduction of the time required for this kind of test, evaluating up to 256 cells simultaneously. Another example, presented in the study conducted by Weng et al. [44], is the implementation of a fast formation protocol, which enables speeding up the evaluation of the internal resistance of the cells, which is strictly related to their capacity.

When comparing the identified approaches, distinct strengths emerge. Machine learning models, especially regression and classification techniques, are well-suited for early defect detection and prediction tasks because they can learn complex, nonlinear patterns from historical data. These methods excel when data availability and quality are sufficient. In contrast, digital twins provide a dynamic, simulation-based approach that is particularly advantageous in scenarios requiring iterative process optimization without physical experimentation, such as tension control or separator positioning. Computed tomography offers high-resolution insights into physical defects but is limited by its higher cost and lower throughput, making it more suitable for offline quality assurance or research applications. Thus, the choice of quality control technology depends on technical capability and the specific application context within the production process.

5. Discussion and summary of studies

To complement the narrative results, Table 4 provides a comparative summary of selected studies, highlighting the production phase, applied method, evaluation approach, and identified limitations. This clarifies how different techniques align with specific production needs and reveals evaluation rigor or scalability disparities. The table also emphasizes which methods are still largely conceptual versus those tested in practical or industrial settings.

Table 4. Used studies overview

Study	Production phase	Method applied	Key findings	Identified limitations
Chen et al. [56]	Electrode manufacturing	Support vector machine (SVM), GPR	Effective in mass loading forecasting	Lab-scale only, no real-time validation
Hwang et al. [25]	Cell assembly	Ultrasonic + Deep learning	Accurate in detecting poor welds	Needs industrial validation
Zhang et al. [24]	Separator control	Virtual quality gates	Improved control and faster decisions	Proof-of-concept only
Evans et al. [23]	Electrode manufacturing	Computed tomography	High-resolution coating error detection	High cost, low throughput
Weng et al. [44]	Cell finishing	Fast Formation protocols	Shortened test time with reliable internal resistance insights	Requires system integration
Lenze et al. [50]	Electrode manufacturing	Simulation + Reparameterization	Improved modeling of calendering effects	Needs validation across setups
Grabmann et al. [14]	Cell assembly	Photodiode + ML	Non-invasive weld quality detection	Signal variability limits robustness

The comparative analysis reveals that each quality method contributes in distinct ways. Machine learning models offer strong predictive power, especially with large datasets, while sensor-driven techniques like ultrasonic or photodiode monitoring effectively detect surface-level defects. Though resource-intensive, computed tomography and digital twins provide deep insights and support process optimization. Notably, the reviewed studies show a trade-off between accuracy and scalability: methods with high precision often lack throughput or real-time capabilities, making them suitable for selective quality gates rather than continuous production monitoring. This evaluation supports a layered quality strategy, combining real-time methods with offline assessments and simulation-based planning.

Despite the promising nature of the given methods, their practical implementation often faces challenges. For instance, machine learning approaches require large volumes of high-quality data, which may not be readily available in industrial settings due to privacy or infrastructure limitations. Similarly, implementing digital twins involves significant initial investments in modeling and simulation capabilities, which may not be feasible for smaller manufacturers. Moreover, many studies demonstrate proof-of-concept solutions in controlled environments, which may not directly translate to full-scale production. Therefore, while the reviewed technologies are theoretically effective, their adoption is often constrained by organizational, technical, and economic factors.

While the reviewed studies provide various technical solutions, several limitations were noted. Many approaches, particularly those involving ML or digital twins, are demonstrated in laboratory-scale settings and lack validation in industrial production environments. Furthermore, there is a noticeable imbalance in the literature, with a stronger focus on electrode manufacturing than other phases such as cell finishing. In some cases, the proposed methods are evaluated on a narrow set of performance metrics without consideration of integration challenges or economic feasibility. These gaps highlight the need for more holistic studies considering the full production lifecycle and including cross-functional performance indicators.

6. Conclusion, limitations, and potential developments

This SLR contributes to the field by identifying dominant trends and techniques in quality control and management for lithium-ion battery (LIB) manufacturing. Key findings include the increasing use of machine learning for predictive quality tasks, the emergence of digital twins for virtual process optimization, and promising applications of computed tomography for high-resolution defect detection. These technologies are primarily concentrated in the electrode manufacturing phase, with fewer studies addressing cell finishing. Overall, data-driven and simulation-based approaches are gaining traction and offer a foundation for more intelligent, efficient battery production systems.

LIBs manufacturing is a complex and costly process due to the high degree of complexity, cause-and-effect relationships among process variables, and strict quality standards. Without a structured and practical approach, it can generate significant scraps. Various quality control and management systems can be implemented to address these challenges. This SLR, conducted following the PRISMA methodology, analysed 46 selected studies from significant research databases, using the JBI quality checklist to evaluate their reliability. The findings highlight key trends, identifying data-driven and ML solutions as the most prominent and investigated approach in literature, together with other promising trends such as simulations and digital twins, computed tomography, multi-criteria optimization, and advanced measurement techniques for charge and discharge currents. A self-evaluation, based on the appropriate JBI checklist for SLRs, was also carried out to identify strengths and limitations, noting that, because the study was realised solely by one researcher, not all the best practices for an SLR could be applied; this is mainly related with potential bias risks arising in the selection of the papers to be included in the review. However, the SLR performed remains unbiased, methodical, and replicable, thanks to the strict adherence to the standards required for the methodology selected, and it can serve as a guideline for future research on the topic.

Despite its methodological rigor, this SLR has several limitations. First, the screening, selection, and evaluation of papers were performed by a single researcher, which introduces potential bias despite efforts to apply objective criteria. Second, the review was limited to English-language publications from 2014 to 2024, possibly excluding relevant studies in other languages or earlier works. Third, the synthesis remains qualitative, as the heterogeneity of methodologies and outcomes prevented a meta-analysis. Finally, many reviewed approaches are theoretical or lab-based, requiring further validation in industrial environments.

Possible improvements include focusing and going more in-depth on specific aspects of LIB production, instead of keeping a broader perspective, and involving multiple authors to enhance research reliability, as suggested by PRISMA guidelines.

Based on the reviewed literature, the following recommendations are proposed. (1) For researchers. Future studies should explore integrating machine learning and digital twins technologies across multiple production phases, emphasizing real-time applications and cross-phase data fusion. More empirical validation in industrial settings is needed to assess scalability and performance. (2) For practitioners. Manufacturers should consider piloting digital quality control systems, starting with high-impact areas such as electrode coating and welding. A combination of predictive analytics and sensor-based feedback loops may yield the best cost-performance trade-off. (3) For policymakers. Funding should support interdisciplinary research that bridges data science, manufacturing engineering, and quality management in battery production, to accelerate the transition from conceptual to applied innovation.

Conflict of interest

The authors declare no competing financial interest.

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