

Review

Digital Twins for Battery Cell Manufacturing: From Process Complexity to Data-Driven Production Optimization

Cristina Herrero-Ponce ^{1,*}, Jorge de Leandro-Tomás ¹ , Virginia Ochovo-Sánchez-Crespo ¹, Leire Zubizarreta ¹, Andrés Lluna-Arriaga ¹, Mayte Gil-Agustí ¹ and Vicente Fuster-Roig ²

¹ Instituto Tecnológico de la Energía (ITE), Avda. Juan de la Cierva, 24, 46980 Paterna, Spain; jorge.deleandro@ite.es (J.d.L.-T.); virginia.ochovo@ite.es (V.O.-S.-C.); leire.zubizarreta@ite.es (L.Z.); andres.lluna@ite.es (A.L.-A.); mayte.gil@ite.es (M.G.-A.)

² Instituto de Tecnología Eléctrica, Universitat Politècnica de Valencia, Camino de Vera s/n Edificio 6C, 46022 Valencia, Spain; vicente.fuster@ite.es

* Correspondence: cristina.herrero@ite.es

Abstract

The growing demand for lithium-ion batteries, driven by the electrification of transportation and the expansion of renewable energy systems, is accelerating the deployment of large-scale manufacturing facilities worldwide. This rapid industrial growth increases the need to ensure high product quality and process reliability, given the complexity and strong interdependence of battery manufacturing stages. In this context, traceability becomes a key requirement for monitoring production processes, detecting deviations, and ensuring consistent performance. Digital twins, defined as virtual representations of physical systems integrating data, models, and simulation tools, are emerging as a promising approach to address these challenges. By enabling enhanced process visibility, predictive capabilities, and decision support, digital twins can contribute to improved control and optimization of battery manufacturing processes. This paper presents a review of current developments in digital twin applications for lithium-ion battery cell production and highlights the potential benefits that these tools can offer to the battery industry, particularly in supporting traceability, process optimization, and quality assurance in next-generation gigafactories. The outcomes of this review provide actionable insights for both academia and industry by identifying research gaps, technological limitations, and opportunities to advance the development and industrial adoption of digital twins in battery cell manufacturing.

Keywords: lithium-ion battery; digital twin; battery manufacturing; process optimization; quality assurance; traceability



Academic Editor: Bo Yang

Received: 22 May 2026

Revised: 25 June 2026

Accepted: 30 June 2026

Published: 2 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Lithium-ion batteries play a key role in enabling the ongoing energy transition. Their global demand is expected to increase significantly, driven by the expanding deployment of renewable energy systems and the widespread electrification of transportation. The energy sector is, therefore, undergoing a profound transformation, which is generating an unprecedented need for large-scale battery energy storage [1,2].

Achieving these production volumes necessitates a substantial increase in global manufacturing capacity. Accordingly, several battery cell gigafactories are presently being developed worldwide. However, ensuring consistent battery cell quality at the industrial scale represents one of the most significant technical challenges limiting the rapid ramp-up of battery cell production in the coming years. In this context, battery cell manufacturing is

often associated with substantial scrap rates, which strongly depend on process maturity. They are typically higher during the early stages of production ramp-up and when new processes or equipment are introduced. Reducing these losses, together with other optimization strategies, will be essential to achieving key industry targets, such as significant cost reductions at the cell level [2–4].

Traceability in complex battery cell manufacturing should be seen not just as a technical data-tracking system, but as a strategic enabler that ensures transparency, quality, safety, and performance throughout the entire lifecycle. It will become a regulatory requirement in the European Union from February 2027 [5], when certain batteries must include a digital battery passport detailing their composition, carbon footprint, and performance, requiring full traceability across the production chain. This regulatory pressure is driving greater supply chain transparency and pushing manufacturers to adopt advanced optimization strategies beyond traditional trial-and-error approaches.

In response to these challenges, there is an increasing need for advanced digital tools capable of improving process understanding, enhancing traceability, and supporting decision-making in complex manufacturing environments. In this context, digital twins have emerged as a promising approach, providing virtual representations of battery manufacturing processes that integrate data, models, and simulation capabilities to enable process monitoring, prediction, and optimization [6]. These dynamic representations act as key tools by combining data and models to simulate, analyze, and optimize production systems. They enable the evaluation of alternative scenarios without disrupting real operations, reducing costs, risks, material waste and energy consumption, while improving efficiency, quality, and sustainability. Structurally, a digital twin integrates the physical process, data acquisition, modelling, and decision-support layers, generating indicators across production, energy, economic, quality and environmental dimensions. Its effectiveness relies on hybrid, multi-paradigm modelling approaches and can evolve from offline analysis tools to fully connected systems, making it a fundamental technology for data-driven, efficient and scalable battery manufacturing.

In recent years, digital twins for batteries have gained strong momentum due to their potential to address challenges across the entire value chain, particularly in manufacturing. In this domain, digital twins are applied to different production stages, from electrode fabrication to cell assembly and full system integration, enabling process modelling, optimization, and quality prediction. Research activities, including European-funded projects, have developed advanced simulation- and data-driven approaches to improve efficiency, scalability, and sustainability, while industrial players such as CATL, LG Energy Solution, and Panasonic have already demonstrated tangible benefits, including enhanced productivity, reduced waste, and higher automation. Overall, these developments show that digital twins are transitioning from research concepts to practical tools for large-scale battery manufacturing.

In this review, the battery cell manufacturing process has been analyzed, considering its sequential structure, inherent complexity, and the strong interdependencies between process stages that ultimately determine product quality and performance. Particular attention has been given to the applicability of digital twin technology within this context, examining how these tools can support process understanding, simulation, optimization, and decision-making in increasingly digitalized and data-intensive production environments.

Building upon this, this review aims to provide a structured and critical synthesis of the advancements in digital twins for battery cell manufacturing. It evaluates current approaches in terms of their capability to represent, monitor, and optimize manufacturing processes across different production stages. Particular attention is given to the level of

integration across the manufacturing chain, as well as to the challenges associated with data management, interoperability, and scalability.

The primary objective of this review is to identify gaps in the existing literature and implementation landscape, especially in relation to fragmented modelling approaches and the limited availability of fully integrated digital twin solutions. By highlighting these limitations and comparing different modelling strategies, this work aims to provide guidance for future research and support the development of more robust, scalable, and industrially applicable digital twin frameworks.

2. Methodology

This study presents a structured literature review aimed at synthesizing the current state of research on the application of digital twin technology in battery cell manufacturing. The methodology, as shown in Figure 1, followed a transparent and reproducible approach inspired by PRISMA guidelines to ensure rigour in the identification, screening, and selection of relevant studies.

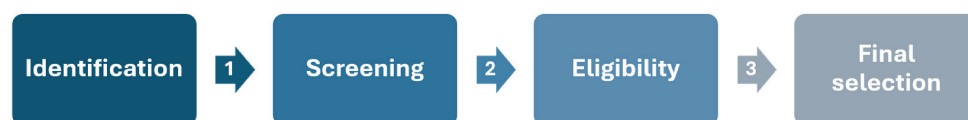


Figure 1. Study selection process following a PRISMA-inspired approach. Source: Own elaboration.

2.1. Literature Search Strategy

The literature search was conducted using major scientific publisher platforms (e.g., ScienceDirect, Wiley Online Library, and MDPI), which provide access to a large body of studies in the peer-reviewed literature indexed in major bibliographic databases. This approach, combined with citation tracking (backward and forward), ensured a comprehensive identification of relevant studies.

The search focused on peer-reviewed scientific articles published in English. A combination of keywords related to the topic was used to retrieve relevant publications. The primary search string included terms such as: “digital twin”, “battery”, “lithium-ion”, “manufacturing”, and “production”.

These keywords were combined and adapted iteratively to capture the different terminologies used in the field. Additional articles were identified through backward and forward citation tracking of relevant papers.

No strict temporal restriction was initially applied in the literature search. However, the analysis revealed that research addressing the application of digital twins specifically in battery cell manufacturing has largely emerged from 2019 onwards. Earlier studies on digital twins were identified mainly in broader industrial contexts, which were considered to establish the conceptual background but fall outside the core focus of this review.

2.2. Eligibility Criteria

To ensure the relevance and focus of the review, inclusion and exclusion criteria were defined as follows:

Inclusion criteria:

- Studies addressing the application of digital twins in battery manufacturing systems.
- Research focused on battery cell manufacturing processes or specific production stages (e.g., mixing, coating, calendaring, and assembly).
- Peer-reviewed scientific articles published in English.

Exclusion criteria:

- Studies focusing exclusively on digital twins for battery operation, performance monitoring, or state estimation (e.g., SoX) without relevance to manufacturing processes.
- Publications not directly related to battery production environments.
- Non-scientific documents or non-peer-reviewed sources.

Some general studies on digital twins in battery systems were considered only to provide contextual background but were not included in the core analysis unless they contributed to manufacturing-related insights.

2.3. Study Selection Process

The selection of studies followed a multi-stage screening process:

1. Title screening: Articles were initially filtered based on their titles to assess their relevance to digital twins and battery manufacturing.
2. Abstract screening: For potentially relevant studies, abstracts were reviewed to further evaluate their alignment with the scope of the review.
3. Full-text assessment: Articles meeting the previous criteria were analyzed in detail to confirm their eligibility and extract relevant information.

This stepwise approach ensured a consistent and focused selection of the literature aligned with the objectives of the review. The final set of analyzed studies consisted of approximately 15 publications.

2.4. Data Analysis and Synthesis

The selected studies were qualitatively analyzed to identify key trends, applications, and technological developments related to digital twins in battery cell manufacturing. Particular attention was paid to:

- The manufacturing stages addressed;
- The functionalities of the digital twin (e.g., simulation, monitoring, and optimization);
- The modelling approach (e.g., physics-based, data-driven, or hybrid);
- The level of implementation (conceptual, experimental, or industrial);
- Reported benefits, limitations, and challenges.

To ensure a consistent and structured analysis, the review was preceded by a preliminary assessment of the battery cell manufacturing process, considering its sequential structure, key operational parameters, and quality-related variables. In parallel, a conceptual overview of digital twins in industrial production was established, including aspects such as adoption drivers, system architecture, modelling approaches (e.g., hybrid and data-driven models), and implementation maturity levels.

This initial framework served as a foundation for the subsequent literature analysis, enabling a process-oriented and application-driven synthesis of the identified studies.

For a more systematic comparison, the reviewed studies were further organized and summarized in a comparative table (see Section 5), including key attributes such as modelling approach and scale, digital twin maturity level, targeted manufacturing stage, main findings, and reported conclusions. This structured representation facilitated the identification of trends, common methodologies, and gaps across different production stages and implementation levels.

The results were therefore analyzed both from a process perspective and from a technological and methodological standpoint, allowing for a comprehensive assessment of the state of the art.

This approach also supported the identification of research gaps and underexplored areas, which are further discussed in Section 6.

3. Battery Cell Manufacturing Process

3.1. Complexity of the Battery Manufacturing Process

The challenge of ensuring battery quality arises from the high sensitivity of electrochemical performance to variations across numerous interconnected process steps. The conventional production of a lithium-ion battery cell mainly comprises three stages, as shown in Figure 2. First, electrodes are manufactured, followed by cell assembly, where electrodes, separators and electrolyte are integrated into the cell. Finally, cell finishing is carried out, including initial electrochemical conditioning.

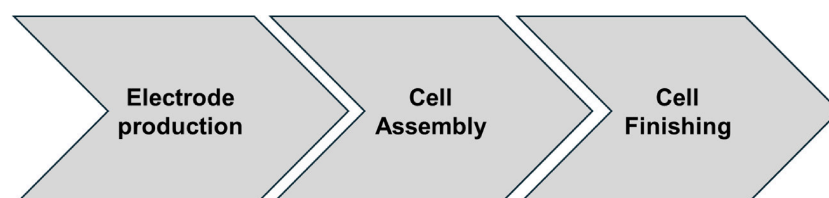


Figure 2. Battery cell manufacturing process breakdown. Source: Own elaboration.

At a higher level, lithium-ion cells are connected in battery modules, which are subsequently assembled into a complete battery pack together with electrical, thermal and mechanical components. Battery production involves a multitude of process variables across all manufacturing stages, each of which can critically influence the final quality of the resulting cells. Moreover, different technical disciplines are involved and a tight integration and coordination across them is required [7–10].

Focusing specifically on battery cell manufacturing, electrode production involves several consecutive process steps, as illustrated in Figure 3. Initially, the different components are mixed to obtain a homogeneous slurry, which is subsequently coated onto the current collector and dried to remove the solvent. Then, calendaring compresses the dried electrode coating to achieve the target thickness, porosity, density, and improved adhesion to the current collector. After calendaring, the electrodes are slit into narrower webs according to the specific battery cell design and are vacuum-dried through a baking step to remove residual moisture [8–10].



Figure 3. Electrode production steps in battery cell production. Source: Own elaboration.

Once the electrodes have been prepared, cell assembly can take place. As displayed in Figure 4, the first step is notching, where individual electrode sheets are cut from electrode webs. The electrodes and separator are then stacked to form the internal structure of the cell, commonly referred to as the jelly roll. Subsequently, the anode and cathode tabs are welded to their respective current collectors, and the jelly roll is transferred into the cell housing. The enclosure is then filled with an electrolyte and hermetically sealed [8–10].

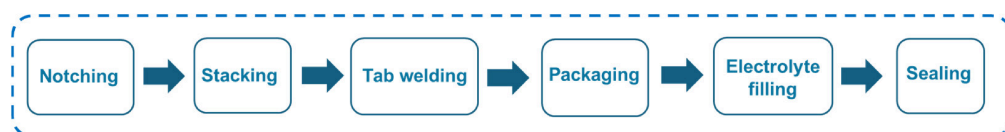


Figure 4. Cell assembly steps in battery cell production. Source: Own elaboration.

Finally, cell finishing includes a series of electrochemical activation and quality control steps, as reported in Figure 5. Prior to formation, an optional pre-treatment step may be carried out to improve electrolyte wetting and facilitate its penetration into the pores of the electrodes and separator. Formation is then carried out to promote the formation of the solid electrolyte interphase (SEI) on the anode surface, which protects it from parasitic reactions with electrolyte components. This layer has a strong influence on the final cell performance. During formation, gas is generated and must be removed under controlled conditions. As part of the electrolyte is consumed during this step, a second round of electrolyte filling is performed, followed by final cell sealing. In the next step, an ageing process is carried out for quality assurance, during which cell characteristics and performance are monitored, typically through regular open-circuit voltage measurements under both high-temperature and room-temperature conditions. Finally, end-of-line (EOL) tests, including pulse tests, internal resistance measurements, optical inspections, open-circuit voltage tests and leakage tests, are conducted. Once all tests have been successfully passed, the cells are packaged and prepared for shipment [8–11].



Figure 5. Cell finishing steps in battery cell production. Source: Own elaboration.

The cell manufacturing process is largely similar across different cell formats, particularly with respect to electrode production and cell formation; however, minor differences arise during the integration stage [7,9].

As already indicated above, the battery manufacturing chain is characterized by numerous sequential process steps, complex interdependencies among these processes, and a high number of adjustable process parameters. Some studies, such as the one conducted by Kampker et al. [12], have identified more than 200 parameters involved across the different manufacturing steps in the pouch cell production process. Although this number may vary depending on the cell format and the manufacturing technologies employed, it highlights the high level of process complexity and the critical need for robust control strategies to achieve final products with the desired quality. Within this framework, the role of traceability becomes particularly critical, as it supports the systematic management of process complexity and sets the basis for the broader considerations discussed in the following section.

Table 1 summarizes the key process and quality parameters associated with the production of prismatic cells, which are considered due to their extensive use in current industrial and commercial battery applications.

3.2. Need for Traceability and Digitalization at Plant Level

In line with the considerations outlined above, traceability in complex manufacturing processes should not be regarded merely as a technical system for data collection and tracking. Rather, it constitutes a strategic enabler for achieving comprehensive process transparency. It enables quality, safety and robustness of battery cell performance over the entire lifecycle.

Battery cell manufacturing is inherently complex, involving a large number of sequential process steps, such as mixing, coating, drying, calendaring, assembly, and formation, that are strongly interdependent. Variations introduced at an early stage, for example in slurry homogeneity or coating thickness, can propagate through the entire process chain and ultimately affect cell quality, performance, and lifetime. This high level of process coupling makes it difficult to isolate the root causes of defects or inefficiencies, as deviations

are rarely linked to a single step but rather to interactions between multiple variables and stages. In such a context, traceability becomes essential, as it enables the continuous tracking of materials, process parameters, and intermediate product states throughout the entire manufacturing chain, allowing manufacturers to reconstruct cause–effect relationships and better understand how local variations impact final outcomes [13].

Table 1. Key process and quality parameters involved in prismatic cell production. Source: Own elaboration.

Manufacturing Stage	Sub Process	Process Parameters	Quality Parameters
Electrode production	Formulation	Material properties Solid content Component ratio	Material purity Batch homogeneity
	Mixing	Time Temperature Dosage Mixing speed Atmosphere Degassing	Slurry homogeneity Viscosity Agglomerates Contamination
	Coating	Geometry Coating gap Web tension Web speed	Thickness Coating uniformity Surface quality
	Drying	Temperature profile Time Air flow	Adhesion Surface quality Residual humidity
	Calender	Pressure Speed Temperature	Porosity Thickness
	Slitting	Cutting speed	Edge geometry Contamination Tolerance
	Baking	Temperature Pressure Time	Residual humidity
	Notching	Cutting speed	Edge geometry Contamination Tolerance
Cell assembly	Stacking	Speed Component positioning Separator tension	Stacking accuracy Electrical insulation
	Tab welding	Ultrasonic welding parameters: frequency, amplitude, pressure, time	Contact resistance
	Packaging	Ultrasonic welding parameters (tabs-cap): frequency, amplitude, pressure, time Laser welding parameters (housing): energy and spot diameter	Seal integrity
	Electrolyte filling	Electrolyte quantity Working pressure	Dosage accuracy
	Sealing	Laser welding parameters: energy and spot diameter	Seal integrity

Table 1. Cont.

Manufacturing Stage	Sub Process	Process Parameters	Quality Parameters
Cell finishing	Pre-treatment	Temperature Time	Uniform electrolyte distribution
	Formation	Current and voltage profiles Time Temperature	Internal resistance Cell capacity after formation
	Degassing	Pressure Temperature	Residual gas in the cell
	Second filling and sealing	Electrolyte quantity Working pressure Laser welding parameters: energy and spot diameter	Dosage accuracy Seal integrity
	Ageing	Initial state of charge Temperature Time Current and voltage profiles	Self-discharge rate Capacity Internal resistance
	End-of-line testing	Testing conditions to be evaluated: internal resistance, capacity, seal integrity, etc.	Quality test compliance

Currently, the need for traceability is further intensified by the limited maturity of large-scale battery production, where high scrap rates and yield losses remain significant challenges. Recent reports [14,15] highlight that scrap rates can range between 15% and 30% during ramp-up and still remain at around 10% in mature production, illustrating the difficulty of maintaining consistent quality in such complex systems. These inefficiencies are largely driven by the strong interdependencies between process parameters, equipment conditions, and material properties, which are often not fully understood or controlled. As a result, improving process transparency through traceable data is a key requirement to identify process instabilities, optimize operating conditions, and reduce waste.

Beyond its influence on battery cell behaviour, traceability is set to become a regulatory requirement for batteries placed on the European Union market from 17 February 2027 onwards. According to the EU Battery Regulation [5], light means of transport (LMT) batteries, industrial batteries with a capacity exceeding 2 kWh and electric vehicle batteries placed on the market or put into service in the European Union must be accompanied by a battery passport containing detailed information on, among other aspects, their composition, carbon footprint, and performance. Compliance with these requirements will require manufacturers to ensure full traceability across the entire battery production process. As an illustrative example, the determination of the carbon footprint demands comprehensive knowledge of the complete production chain, including the accurate identification and quantification of materials and energy inputs and outputs at all stages of battery manufacturing.

In this regulatory context, increasing oversight from the European Union is driving manufacturers to ensure greater transparency across the entire supply chain.

In addition to enhancing traceability across the value chain, the implementation of new optimization strategies within the production process is also required, as strategies that rely solely on empirical and experience-based approaches are no longer sufficient. Moving beyond traditional trial-and-error approaches is essential to enable effective process optimization, and automation supported by digitalization constitutes a fundamental lever for enhancing process control, performance, and overall manufacturing efficiency. At

present, although significant progress has been made in data acquisition technologies (e.g., sensors, MES, and SCADA), many manufacturing systems still struggle with fragmented data silos and limited integration across process steps. This hinders the ability to fully exploit traceability, as data are often collected but not effectively connected or analyzed in a holistic manner [16].

Digitalization tools enhance the understanding of interactions between process and product quality by transforming a physical product into a virtual representation, thereby enabling efficient data transfer, storage, and processing. Such virtual replicas have a significant impact on the development and optimization of battery systems, as they enable real-time process monitoring as well as process simulation and optimization. This represents a substantial step beyond traditional process and product optimization approaches based on trial-and-error methodologies. The implementation of digitalization within battery cell production is therefore associated with shorter time-to-market and cost reductions, driven by the reduced need for physical prototyping during iterative optimization and redesign stages until the desired final quality is achieved. Consequently, digitalization emerges as an essential tool for addressing the challenges of large-scale battery production and for accelerating the industrial ramp-up [12,17–19].

4. Digital Twins in Industrial Production

4.1. Motivation for the Adoption of Digital Twins

As discussed in the previous sections, battery manufacturing is characterized by a high number of sequential stages, strong interdependencies between process variables, and increasing requirements for traceability, transparency and regulatory compliance. However, the availability of traceable and digitalized data does not, by itself, ensure a better understanding or optimization of the manufacturing system. The main challenge is to transform heterogeneous process, quality, energy and operational data into actionable knowledge that can support decision-making in complex production environments [17]. In this context, the role of digital twins is not limited to storing or visualizing traceability data; rather, they provide a framework to move from descriptive digitalization towards predictive and, in more advanced implementations, prescriptive process support.

A digital twin can be defined as a virtual representation of a physical asset, process or system that combines data and models to reproduce its behaviour, analyze its operation and simulate alternative scenarios. In the manufacturing context, this concept should not be limited to a static digital replica but rather understood as a dynamic decision-support tool capable of linking the physical and virtual domains. This interpretation is especially relevant in industrial environments, where the value of the digital twin depends not only on the fidelity of the model, but also on its ability to provide useful information for operational and production decisions, improve energy efficiency and energy costs, contribute to sustainability criteria, and support a broader strategy of production effectiveness in the context in which it is applied.

In battery production, this capability is particularly relevant because process optimization is difficult to address exclusively through physical experimentation as described above. Battery cells are highly sensitive to small variations introduced across interconnected manufacturing steps, and these variations may propagate through the process chain until they affect final cell quality, reliability and lifetime. Changes in process parameters, production scheduling, equipment configuration or resource allocation may affect cell quality, production throughput, energy consumption and material losses. This limitation becomes particularly relevant during ramp-up, process reconfiguration or equipment adjustment, where incomplete knowledge of cause–effect relationships and unstable operating conditions may increase the risk of rejected batches, additional resource consumption and

prolonged optimization cycles. Recent studies on lithium-ion battery material flows identify manufacturing scrap as a significant production-related stream arising from trimmings, process start-ups and off-specification parts. Process-yield assumptions reported in the literature show losses across several manufacturing steps, with yields varying depending on the material and process stage, and scrap rates commonly modelled as decreasing from high start-up values to lower mature-production levels as experience is gained. As indicated in a previous section, scrap rates in mature cell production are around 10%. These reported rates confirm that manufacturing losses are not marginal in battery cell production and illustrate the relevance of improving process control, reducing trial-and-error approaches and supporting yield-oriented decision-making in physical production environments [20]. A digital twin provides a controlled virtual environment in which such alternatives can be evaluated before their implementation in the real manufacturing system. In this sense, it acts as a what-if analysis environment, where different operating conditions can be explored, compared and prioritized according to selected performance indicators [21].

In addition to operational efficiency, digital twins are also motivated by the need to reduce material and energy waste. Battery manufacturing involves high-value materials and energy-intensive stages, so deviations in process conditions or inefficient operation may have a direct impact on production costs and environmental performance. This energy dimension is particularly relevant because battery cell production requires substantial energy inputs, which are directly linked to operating costs and greenhouse gas emissions. At a macroeconomic level, recent analyses indicate that the future production of lithium-ion and post-lithium-ion battery cells may require very large amounts of energy if no production improvements are implemented, whereas process optimization measures could substantially reduce this demand. In this context, a digital twin can help evaluate how different operating strategies affect scrap generation, energy use, equipment utilization and process stability, providing a basis for selecting more efficient production scenarios [22].

From an energy-efficiency perspective, the digital twin becomes especially valuable when energy consumption is not treated as an isolated or aggregated variable, but as a dynamic consequence of production decisions, machine states, process parameters and external operating conditions. Previous work on Industrial Digital Energy Twins [23] has shown that these tools can be used to predict energy consumption and costs while evaluating the behaviour of the process under productive changes, with the aim of improving consumption optimization, production efficiency and process flexibility.

Therefore, the motivation for applying digital twins to battery manufacturing lies in their ability to connect digitalized and traceable process information with simulation, prediction and decision-support capabilities aimed at improving process design and optimization. These tools provide a framework to analyze alternative production scenarios, anticipate the impact of operational decisions, reduce the risks associated with trial-and-error approaches, and support improvements in lead time, resource efficiency, energy consumption and material utilization. However, their contribution should be understood as dependent on the quality and representativeness of the available data, the validity of the underlying models, and the degree of integration between the virtual environment and the physical manufacturing system. This justifies their use as a key enabling technology for moving towards more transparent, efficient and data-driven battery manufacturing systems.

4.2. Structure of the Digital Twin

As outlined in the previous section, a digital twin can be understood as a virtual representation of a physical system built upon data, models, and simulation tools, the value of which extends beyond mere replication to support analysis, prediction, optimization, and decision-making [24]. This interpretation is consistent with the foundational digital

twin literature, which frames the concept as a coupled physical–virtual system in which the digital representation is not only used to reproduce the physical entity but also to support understanding, anticipation and improvement of system behaviour. Grieves et al. [25] emphasized the relevance of digital twins for managing complex systems and mitigating undesirable emergent behaviour, while Tao et al. [26] further developed the concept for product design, manufacturing and service, highlighting the integration of physical entities, virtual entities, data, connections and services as core elements of digital twin implementation.

In this sense, its structure must be examined through the relationships that define it. An isolated simulation or a static digital model does not necessarily constitute a digital twin. A useful distinction can be made between a digital model, a digital shadow and a digital twin. A digital model represents a physical object or process in virtual form but does not include automatic data exchange with the physical system. A digital shadow incorporates unidirectional data flow from the physical system to the virtual model, so that the model can be updated from observed or monitored data. In contrast, a digital twin requires a higher level of integration, in which the physical and virtual domains are connected through periodic or real-time data exchange, and, in more advanced implementations, the virtual model can support recommendations or actions that are fed back to the physical system. This distinction is summarized in Table 2.

Table 2. Conceptual distinction between digital model, digital shadow and digital twin. Source: Authors’ own elaboration based on Kritzinger et al. [27].

Concept	Connection with Physical System	Data Flow	Update Level	Decision-Support Capability
Digital Model	No automatic connection with the physical system	No automatic data exchange	Manual or occasional update	Limited; mainly used for offline analysis or design support
Digital Shadow	Physical system connected to the virtual model	Unidirectional, from physical to digital	Periodic or real-time update from monitored data	Moderate; supports monitoring, diagnosis and analysis
Digital Twin	Coupled physical–virtual system	Bidirectional or functionally closed-loop in advanced implementations	Periodic or real-time update, with potential feedback on the physical system	High; supports prediction, scenario analysis, optimization and decision-making

For a model to be considered a digital model, there must be a functional relationship between the physical system to be represented, the virtual model that reproduces its behaviour, the data used to characterize or update it, and the use of the results to support operational or strategic decisions. This functional relationship should be understood not only as the existence of a model, but also as the existence of a defined information flow, with a given update frequency and directionality, ranging from periodic unidirectional monitoring to bidirectional closed-loop interactions. Therefore, the digital twin differs from a conventional simulation because it is oriented towards representing the real behaviour of the system and evaluating alternative scenarios according to criteria defined by the user or by the needs of the process.

From a structural perspective, an industrial digital twin requires the coherent integration of several essential elements: a physical process or real system that constitutes the object of representation, a digital model capable of reproducing the relevant aspects of its behaviour, operating data from historical, experimental, real-time monitored or expert-

estimated sources, a functional interconnection between physical reality and the virtual environment, and a user, process manager or decision-making system that interprets the results generated by the model and transforms them into improvement actions [28]. In this architecture, the interconnection between the physical and virtual domains should be understood according to the level of integration described above, including the directionality of the data flow, the update frequency and the possible existence of feedback from the virtual model to the physical system. Under this logic, these elements can be organized through a layered architecture: the first layer corresponds to the physical process, where operational data are generated and the phenomena to be represented take place; a second layer is oriented towards data acquisition, processing and integration, including production, energy, quality, machine-state and external-condition signals; a third layer constitutes the modelling and simulation core, where the relevant behaviours of the system are reproduced and its main variables are reconstructed; and finally there is an analytical and interaction layer aimed at visualizing results, comparing scenarios, calculating indicators and supporting decision-making. Depending on the maturity level of the implementation, this final layer may range from offline what-if analysis performed by engineers to online decision-support tools or closed-loop recommendations transferred back to the production system. In the case of digital twins oriented towards efficiency, this architecture can rely on an energy-productive model that acts as the simulation core and integrates productive logic with the energy behaviour of the process [23]. This conceptual structure is summarized in Figure 6.

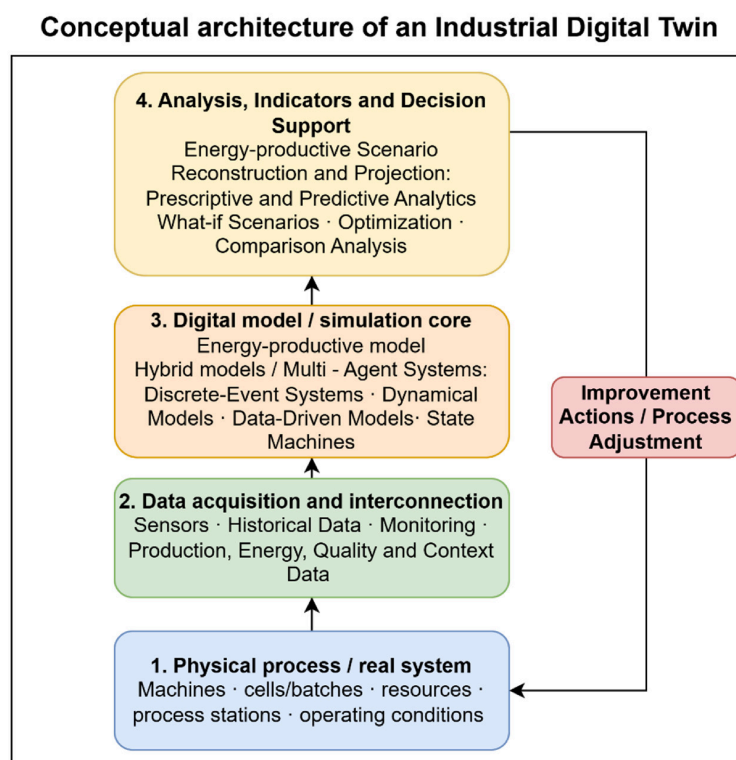


Figure 6. Conceptual architecture of an industrial digital twin, structured around the physical process, data acquisition and interconnection, the digital simulation core, and the analysis layer for decision support and process improvement. Source: Own elaboration.

The usefulness of this architecture is reflected in the generation of performance indicators that allow the process to be evaluated from different perspectives. These indicators are not limited to production variables, but can also integrate energy, economic, environmental and quality-related information. This is particularly relevant in battery manufacturing,

where production performance, energy demand, material losses and quality outcomes are strongly interrelated. In this way, the digital twin enables the comparison of alternative scenarios under multiple criteria and supports more comprehensive decision-making. Table 3 summarizes the main categories of indicators that can be generated or supported by an industrial digital twin.

Table 3. Main categories of indicators generated or supported by an industrial digital twin. Source: Own elaboration.

Indicator Category	Examples	Utility Within the Digital Twin
Productive indicators	Lead time, throughput, equipment utilization, station occupancy, OEE	Evaluate production performance, identify bottlenecks and compare process configurations.
Energy indicators	Total energy consumption, specific energy consumption per cell or batch, peak power demand	Analyze the energy impact of production scenarios and identify inefficient operating conditions.
Economic indicators	Energy cost, cost per batch, cost per cell produced, operational cost variation	Assess the economic impact of alternative planning or operating strategies.
Quality and material indicators	Scrap rate, rejected cells, process stability, deviations from target conditions	Relate process decisions with quality losses, material waste and production robustness.
Environmental indicators	Associated emissions, energy-related carbon footprint, resource efficiency	Evaluate sustainability impacts and compare scenarios from an environmental perspective.
Decision-support indicators	Scenario ranking, improvement potential, sensitivity to process parameters	Prioritize alternatives and support operational or strategic decision-making.

4.2.1. Hybrid and Multi-Paradigm Modelling Approach

One of the most relevant aspects of this architecture is the need to adopt a hybrid and multi-paradigm approach in which different agents and modelling logics can be coordinated to represent the behaviour of the process across different dimensions, time scales and operating states. In battery manufacturing, this need is particularly evident because the production system combines discrete flows of cells, batches, equipment occupation and process sequences with continuous or quasi-continuous phenomena such as thermal behaviour, energy demand, material transport, electrochemical evolution and quality degradation mechanisms. The flow of products, batches, queues, resources, waiting times and production sequences can be represented through discrete-event simulation. In contrast, variables such as energy consumption, power curves, transition times, temperatures, flow rates or the dynamic states of equipment usually require continuous models, system dynamics or simplified physical equations. When sufficient and representative data are available, data-driven models, artificial intelligence or machine learning techniques can be incorporated to capture nonlinear relationships that are difficult to formulate using conventional physical models [24]. Therefore, the role of a hybrid digital twin is not to replace one modelling paradigm with another, but to combine them according to the physical, operational and data-driven nature of each phenomenon represented.

The methodological justification for this multi-paradigm approach lies in selecting the most suitable modelling method for each part of the production system, considering the required level of detail, data availability, computational complexity, model validation effort and the purpose of the analysis. This selection must also consider the maturity of the available data and the intended use of the model: for example, offline scenario comparison may tolerate simplified models, whereas online prediction or closed-loop decision support requires higher robustness, validation and synchronization with the physical process. In this sense, the objective is not to develop the most complex model possible, but to achieve a balance between representativeness and usefulness, so that the digital twin is sufficiently accurate to answer relevant industrial questions without generating an unnecessary burden of development or validation. This balance is especially important in battery manufacturing, where excessive model complexity may limit industrial applicability, while overly simplified models may fail to capture relevant interactions between production performance, energy consumption and cell quality.

This need to combine modelling approaches can also be supported by multi-agent systems when the production process involves multiple entities with differentiated states, behaviours and interactions. Machines, batches, cells, human resources, process stations, buffers or auxiliary systems can be modelled as agents with specific states, behavioural rules and relationships. This approach is useful for capturing the interaction between productive resources, operational constraints, process events and energy variables, especially when local decisions or state changes affect the behaviour of the overall system. However, multi-agent modelling should not be interpreted as a universally superior alternative to other distributed modelling approaches. Its suitability depends on the degree of autonomy of the entities represented, the relevance of their interactions, the availability of data for calibration and the complexity that can be reasonably validated in an industrial environment. Under these conditions, it can contribute to scaling the digital twin from individual equipment to a complete production line or plant while maintaining a modular and adaptable structure [29].

From the perspective of energy efficiency, this structure acquires specific value because it allows the productive dimension to be integrated with the energy and economic dimensions of the process. Energy consumption should not be treated only as an aggregated value measured at the end of a given period, but as a dynamic variable associated with machine states, production sequences, waiting times, start-ups and shutdowns, external conditions, and resource utilization. In this way, an energy-productive digital twin makes it possible to relate operational decisions to indicators such as energy consumption, cost, kWh per cell or batch, equipment utilization, productivity, lead time, OEE, or environmental impact. This integration enables planning and operational decisions to be evaluated not only from a productive point of view, but also according to energy and sustainability criteria.

4.2.2. Data-Driven Models and AI Integration

The integration of data-driven models, artificial intelligence and machine learning techniques is a key component of digital twin frameworks oriented towards process optimization. This is not a new topic in battery manufacturing, since the recent literature has already mapped the application of machine learning methods to lithium-ion battery cell production, including the analysis of product parameters, process parameters and adopted algorithms [30]. While physical, discrete-event or system-dynamics models are useful for representing known mechanisms and operational logic, data-driven models can complement them by identifying patterns, correlations and nonlinear relationships that are difficult to describe through conventional equations. In battery manufacturing, these techniques can support soft sensing, sensor fusion, anomaly detection, quality prediction,

defect identification, energy-consumption forecasting, process-parameter optimization and the development of surrogate models that reduce the computational burden of detailed simulations [16,18].

However, the use of AI and machine learning within digital twins should not be understood as an automatic improvement of the model. Their reliability depends on the availability of representative and well-labelled datasets, the quality and synchronization of process data, the interpretability of the models, and their ability to generalize beyond the operating conditions used for training. This is particularly relevant in battery manufacturing, where small variations in process parameters may affect cell quality and where experimental validation can be costly and time-consuming. Therefore, data-driven models should be integrated into the digital twin as part of a validated hybrid framework, combining process knowledge, physical understanding and industrial data rather than replacing them. In this sense, AI-driven digital twin frameworks can support predictive maintenance, quality control and process optimization, but their industrial value depends on their validation, integration with production data and ability to provide reliable decision-support outputs [18].

4.2.3. Digital Twin Maturity Levels and Implementation Challenges

The structure of the digital twin may evolve through different maturity levels depending on its degree of connection with the real plant and its decision-making capability as shown in Figure 7. It can begin as a disconnected or offline model, useful for understanding the process, analyzing scenarios, validating hypotheses, and comparing alternatives without directly intervening in the physical system. It can then evolve towards a digital shadow or an online digital twin, capable of incorporating periodic or real-time data from sensors, databases, MES, SCADA, IoT platforms or other industrial systems. In more advanced stages, the digital twin can support closed-loop decision-making, where recommendations or optimized setpoints are transferred back to the production system and may eventually contribute to autonomous or self-optimizing manufacturing environments.

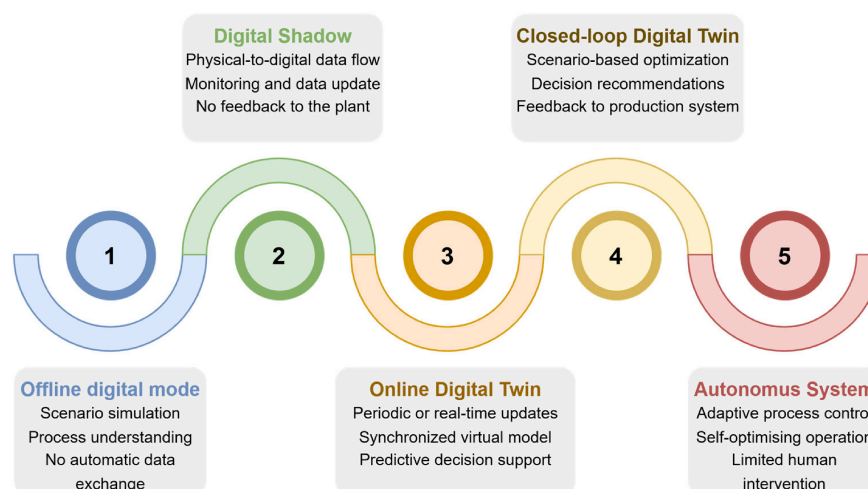


Figure 7. Roadmap of digital twin maturity in industrial battery manufacturing: from offline digital models to digital shadows, online digital twins, closed-loop decision support and autonomous or self-optimizing manufacturing systems. Source: Own elaboration based on Tao et al. [26] and Kritzinger et al. [27].

Despite these potential benefits, the implementation of digital twins in battery manufacturing still involves significant challenges. These include data quality and completeness, synchronization between physical and virtual systems, model calibration and validation, computational cost, interoperability with MES, SCADA, ERP and IoT infrastructures, cyber-

security, scalability to gigafactory-level production and the need for standardized interfaces and modelling practices. These limitations are particularly relevant in battery manufacturing because process conditions, quality outcomes and energy performance are strongly interdependent and may vary across production scales, equipment configurations and cell chemistries.

Applied to battery manufacturing, this approach provides a suitable methodological basis for representing sequential, interdependent, traceable, and energy-intensive processes. The combination of models, data, scenario simulation, and decision criteria makes it possible to address the complexity of the production process without reducing the digital twin to a mere visual representation.

5. Digital Twins in Battery Cell Production: Current Developments and Limitations

In recent years, research on digital twins for batteries has intensified, motivated by the significant potential of this technology for the battery industry, as discussed throughout the article. Based on the studies conducted in the literature, battery digital twins can be employed for multiple applications, depending on the specific objectives and scope of their implementations. The literature demonstrates that digital twins in battery systems have been explored across various domains; however, their application to cell manufacturing remains comparatively less mature and more fragmented.

The developments reported in the literature address a variety of use cases, ranging from battery design and manufacturing to battery monitoring, predictive maintenance, and the estimation of state variables (SoX), among other applications [31].

In line with the focus of this review, this section critically reviews digital twin approaches specifically developed for lithium-ion battery cell manufacturing, with emphasis on their modelling capabilities, level of validation, and integration across process steps.

Within cell manufacturing, existing digital twin developments predominantly target individual process steps rather than fully integrated process chains. Existing developments range from digital twins focused on specific processes within electrode manufacturing to those that model cell assembly and integration, and even extend to higher system levels such as complete battery packs.

A substantial body of work has focused on physics-based modelling approaches that can support or enable digital twin development at the process level.

In this context, Lombardo, T. et al. modelled the slurry phase using Coarse-Grained Molecular Dynamics (CGMD) [32] and subsequently proposed in other work a three-dimensional drying model specifically focused on carbon-binder migration phenomena [33]. Furthermore, Ngandjong AC et al. [34] implemented a Discrete Element Method (DEM) model to simulate the calendaring process for battery electrodes, representing a step toward process-level digital twin development for lithium-ion battery manufacturing. In addition, Shodiev, A. et al. [35–37] developed models for electrolyte filling based on the Lattice Boltzmann Method, while Chouchane, M. et al. [38] reported a model to assess the impact of the carbon-binder spatial location on the electrochemical performance of the electrode.

As reflected in Table 4, these studies predominantly operate at the particle and electrode scales and are typically characterized by relatively low-to-intermediate maturity levels (TRL 2–4), despite offering high physical fidelity. This highlights a key trade-off in current digital twin development: while physics-based models provide detailed insight into process-induced microstructural features, their integration into scalable and fully operational digital twins for manufacturing remains limited.

Table 4. Overview of modelling approaches and digital twin implementations in battery manufacturing across different scales and maturity levels. Source: Own elaboration.

Modelling Approach/Scale	Maturity Levels	Manufacturing Stage	Key Finding	Conclusions	Reference
Coarse-grained molecular dynamics/particle mesoscale	TRL 2–3 physics-based model development; no industrial integration	Slurry preparation	Modelling how particle interactions affect microstructure	Provides a detailed representation of mesoscale interactions during slurry formation, making it highly valuable for fundamental insights, although further developments are required to enhance its scalability towards industrial digital twin application	Lombardo et al., 2020 [32]
3D drying model/electrode	TRL 3 (validated at component level; limited experimental comparison)	Drying	Predicts binder migration and heterogeneity formation	Effectively captures carbon-binder migration and associated heterogeneity, offering valuable insight into drying processes, while additional work could improve its applicability at larger scales and under industrial conditions	Lombardo et al., 2021 [33]
Discrete element method/electrode	TRL 3–4 (experimentally validated at lab scale; partial process representation)	Calendering	Simulates densification and particle rearrangement	Demonstrates strong capability in describing particle rearrangement and mechanical behaviour during calendering, particularly when supported by experimental calibration, with ongoing efforts needed to facilitate its integration into continuous manufacturing environments	Ngandjong et al., 2021 [34]
Computational fluid dynamics (lattice Boltzmann method)/electrode	TRL 3 (validated at model level; sensitive to input microstructure)	Electrolyte filling	Models wetting and transport in porous media	Offers a robust framework for modelling electrolyte infiltration in complex porous structures, although its predictive capability is closely linked to the accuracy of the underlying microstructural inputs	Shodiev et al., 2022 [35–37]
Microstructure-resolved electrochemical model/electrode and cell	TRL 3–4 (lab-scale validation; limited manufacturing coupling)	Electrode production	Explicitly resolves carbon-binder domain (CBD) distribution and its impact on transport pathways and electrochemical behaviour	Successfully links electrode microstructure to electrochemical performance, contributing to bridging manufacturing and operation, while its effectiveness depends on the accuracy of upstream process descriptions	Chouchane et al., 2019 [38]

Table 4. Cont.

Modelling Approach/Scale	Maturity Levels	Manufacturing Stage	Key Finding	Conclusions	Reference
Data-driven modelling of battery cell production processes using machine learning techniques/cell	TRL 3–4 (validated at lab scale with data-driven models; limited integration into full manufacturing chains)	Cell manufacturing (process optimization and quality prediction)	Applies machine learning models to capture relationships between process parameters, product quality, and performance	Provides an efficient and scalable approach for process optimization and quality prediction, suitable as an enabling component for digital twin implementation, although it is dependent on data availability and limited in physical interpretability	Haghi et al., 2023 [30]
AI-driven digitalization framework for lithium-ion battery manufacturing based on integration of process data and machine learning models	Process TRL 3–4 (data-driven framework validated at lab/industrial data level)	Electrode manufacturing (process optimization and quality prediction)	Applies machine learning models to capture relationships between process parameters and manufacturing outcomes, enabling predictive optimization and reduced experimental effort	Highly effective for process optimization and quality prediction with strong scalability potential, although it is limited by reliance on data-driven correlations, lack of process-resolved physical modelling, and incomplete integration into full digital twin systems; optimizing lithium-ion battery manufacturing with digitalization and AI-driven frameworks	Manoharan et al., 2026 [18]
Kinematic and physics-based simulation model/manufacturing machinery	TRL 4–5 (validated in relevant environment; prototype implementation)	Cell assembly (stacking of pouch cells)	Enables predictive modelling of motion sequences and web tension behaviour in flexible electrode stacking processes	Highly suitable for machine-level optimization and design validation, demonstrating strong predictive capability for assembly processes, while remaining specific to the investigated system configuration	Husseini et al., 2022 [21]
Hierarchical and modular digital twin architecture based on intermediate product-level (sub-cell) representations across the manufacturing chain	TRL 3–4 (framework defined with partial implementation and limited validation of interconnected sub-models)	Full production chain	Enables representation and tracking of intermediate product states through interconnected sub-cell twins for predictive quality assessment and process linking	Effectively combines modelling and sensing to support advanced manufacturing strategies such as zero-defect production, with continued progress depending on data quality and integration robustness	Ludwigs et al., 2021 [19]

Furthermore, the analysis reveals that the coupling between manufacturing processes and final cell performance, although addressed in works such as those by Chouchane et al. [38], is still not systematically integrated across the full production chain. Consequently, most existing approaches can be considered building blocks rather than complete digital twins, reinforcing the need for multiscale and interoperable frameworks.

In addition to physics-based modelling approaches, recent studies have explored the use of machine learning to support battery cell production processes. In this context, Haghi et al. [30] reviewed the application of data-driven models to capture the relationships between process parameters, product quality, and performance within cell manufacturing. Their work describes that machine learning techniques can enhance predictive capability and reduce the need for extensive experimental campaigns, enabling more efficient process optimization. These approaches provide computationally efficient and scalable representations of manufacturing systems, making them particularly suitable as data-driven modelling components that could be integrated into future digital twin implementations. However, their effectiveness remains closely linked to the availability and quality of data, and their limited physical interpretability highlights the need for integration with physics-based models in order to support more comprehensive digital twin frameworks.

Another study performed by Manoharan et al. [18] presents a data-driven approach aimed at improving manufacturing performance through the integration of artificial intelligence and digitalization strategies. The authors propose a framework that combines process data with machine learning models to enable predictive optimization of key manufacturing parameters, with a particular focus on enhancing process efficiency and product quality. Unlike physics-based modelling approaches, the framework relies primarily on data-driven correlations to capture process–performance relationships, allowing rapid exploration of operating conditions and reduced experimental effort. However, while the study demonstrates the potential of AI-driven methodologies to support manufacturing optimization, it does not provide a fully integrated digital twin implementation, as it lacks detailed process-resolved modelling and comprehensive validation across multiple manufacturing stages. As such, the work is best interpreted as an enabling step towards digital twin development, illustrating how data-centric approaches can support decision-making in battery manufacturing while highlighting the need for stronger integration with physics-based models and multiscale digital twin frameworks.

A major effort to integrate modelling approaches for battery manufacturing is represented by the ARTISTIC Battery Manufacturing Digitalization Initiative, as reported by Troncoso et al. [39], where a comprehensive digital ecosystem for battery manufacturing has been established, combining experimentally validated 3D physics-based mesoscale models, machine learning (ML), and multi-objective optimization algorithms. These tools enable the simulation of key electrode manufacturing processes, such as drying and calendaring, and the prediction of how processing parameters affect electrode mesostructure and cell performance. The framework is further extended with immersive visualization technologies (VR/MR) for data exploration and training, representing a novel aspect in the battery field. Altogether, ARTISTIC demonstrates a hybrid modelling paradigm that integrates physics-based understanding with data-driven acceleration, aiming to reduce development time and cost and improve reliability.

At the same time, the project highlights important challenges associated with advanced digital approaches. The combination of multiphysics models, ML, and optimization workflows introduces significant complexity in terms of calibration, validation, and computational cost. Moreover, despite the strong proof-of-concept results, the transition toward industrial deployment remains non-trivial, requiring advances in software engineering, standardization, and closer collaboration with industry. ARTISTIC therefore exemplifies

both the potential and current limitations of digitalization in battery manufacturing, bridging fundamental research and application, but also revealing the gap that still exists for scalable and fully deployable industrial solutions.

In this context, higher-maturity digital twins are more frequently observed at the machine or system level, where direct validation and real-time data integration are feasible, whereas process-resolved and microstructure-based models remain predominantly at the research stage. This imbalance, also highlighted in Table 4, underlines a critical gap between model fidelity and industrial deployability.

Building upon the process-level modelling approaches discussed above, recent developments have progressively shifted towards higher levels of abstraction, where digital twins are implemented at the machine and system levels within battery cell manufacturing. As highlighted in Table 4, this transition reflects a broader trend in the field: while earlier studies focus on high-fidelity descriptions of individual manufacturing steps, more recent contributions increasingly address the integration of these processes into operational environments, in some cases supporting monitoring, validation or process optimization at machine or system level.

This evolution also reveals a fundamental distinction in current digital twin development. On the one hand, physics-based models provide detailed insight into process–structure relationships at the material and electrode scales, albeit with limited maturity and integration. On the other hand, system-level digital twins achieve higher readiness levels by focusing on machine behaviour and process control, often relying on simplified representations. Consequently, the literature suggests a complementary, yet still weakly connected, landscape in which multiscale integration remains a key challenge for achieving fully functional digital twins in battery cell manufacturing.

Henschel et al. [40] analyzed the potential of digital twin technology and reviewed its possible applications within battery cell manufacturing. Their analysis highlights the potential of digital twins to enable a transition from conventional batch-based processing towards more flexible and continuous manufacturing paradigms, particularly in electrode fabrication and assembly stages.

Other studies, such as the work by Hussein et al. [21], focus on the cell assembly stage. In this case, the authors develop a digital twin that represents a machine for flexible cell stack formation of pouch cells, which can be used to optimize both process parameters and the current machine design. First, a kinematic process model was developed to visualize and verify the system’s motion sequences in a virtual environment. Subsequently, a simulation model was established to predict web tension by accurately representing the key machine components and material behaviour. The model’s validity was confirmed through a series of experimental tests. As reflected in Table 4, these contributions represent higher levels of maturity compared to process-resolved models, as they operate at the machine and system levels and are supported by experimental validation. In particular, the work by Hussein et al. [21] demonstrates that digital twins at the assembly stage can achieve TRL 4–5 due to their direct integration with real equipment and measurable process variables. However, in contrast to physics-based models at the material and electrode scales, these approaches typically rely on simplified or system-level representations, focusing on operational optimization rather than detailed process physics. This distinction highlights a complementary relationship between high-fidelity process models and higher-maturity system-level digital twins.

Furthermore, Ludwigs et al. [19] propose a digital twin framework for battery cell production with a particular emphasis on predictive quality assessment. A corresponding digital twin architecture is established based on defined requirements and key parameters, enabling production optimization measures such as predictive quality. The approach relies

on individual (sub-cell) twins that represent distinct intermediate products within the manufacturing process.

Beyond the cell level, other works address the development of digital twins for battery modules and battery pack production. At the module level, Sharma, A. et al. [41] propose a digital twin approach for fast and cost-effective assembly of electric vehicle battery modules. Based on digital twin-driven design and simulation, a robotic assembly line was developed for battery module production at different scales. At the pack level, Li, C. et al. [42] simulate a battery pack production line supported by digital twin technology.

Moreover, only a limited number of studies, such as Ludwigs et al. [19], attempt to bridge multiple stages of the manufacturing chain through hierarchical digital twin architectures. Nevertheless, the integration of process-level models into such frameworks remains limited, indicating that most existing approaches represent isolated implementations rather than fully integrated digital twins for cell manufacturing. Overall, the current literature reveals a clear trade-off between model fidelity and maturity: while system-level digital twins achieve higher readiness and practical applicability, their connection to underlying process physics remains incomplete, emphasizing the need for multiscale and interoperable digital twin frameworks.

In parallel to the scientific literature discussed above, recent research and innovation initiatives have increasingly focused on the development of digital twin concepts for battery manufacturing, reflecting a strong industrial and strategic interest in this field.

However, in contrast to the peer-reviewed studies analyzed, these initiatives are often characterized by a limited availability of fully described and validated modelling approaches in the open scientific literature. As a result, their contributions are typically not directly comparable to the process- and system-level digital twins reported in academic publications.

As reflected in the literature review performed in the work, this distinction highlights a gap between ongoing industrial developments and publicly available scientific models. While these initiatives frequently target higher levels of integration, scalability, and real-time applicability, their underlying modelling strategies are not always described in sufficient detail to enable critical assessment or reproducibility. Nevertheless, these efforts provide valuable insight into the direction of the field, emphasizing the importance of data integration, hybrid modelling approaches, and end-to-end process connectivity for future digital twin implementations in battery cell manufacturing. This divergence between academic and industrial developments further reinforces the need for transparent, validated, and interoperable modelling frameworks capable of bridging high-fidelity process descriptions with scalable manufacturing-oriented digital twins.

Beyond the developments reported in the academic literature and projects, several industrial studies and reports indicate a growing adoption of digital twin technologies within battery cell manufacturing environments, providing complementary evidence of their practical relevance.

Contemporary Amperex Technology Co., Limited (CATL) has described the deployment of advanced smart manufacturing solutions at its Yibin production facility, integrating artificial intelligence, Internet of Things technologies, and flexible automation aimed at improving production efficiency, process stability, and product quality through data-driven control and automation.

Reported performance indicators suggest measurable improvements, including increases in production line speed on the order of 10–20% and reductions in yield losses of approximately 10–15%, although these values should be interpreted cautiously due to limited methodological transparency.

These developments are also associated with increased levels of automation and operational flexibility, consistent with the expected capabilities of digital-twin-enabled manufacturing systems.

Similar digitalization strategies combining data analytics, advanced control systems, and virtual representations of manufacturing processes have been reported across major battery manufacturers, including LG Energy Solution, Samsung SDI, and Panasonic, although detailed technical descriptions are generally not publicly available in the peer-reviewed literature.

While these industrial examples provide quantitative indications of performance improvements, they also highlight an important limitation when compared to academic studies: the lack of detailed methodological disclosure, which restricts reproducibility and critical assessment. As a result, and as already suggested by the analysis in Table 4, such industrial implementations cannot be directly compared with physics-based or system-level digital twin models reported in the scientific literature. Instead, they should be interpreted as evidence of the technological relevance and industrial potential of digital twins, rather than as validated modelling frameworks. Nevertheless, the reported improvements in throughput, yield, and operational flexibility are consistent with findings from recent academic studies on data-driven and hybrid digital twin approaches, which also demonstrate measurable gains in process optimization and quality control under controlled conditions.

6. Conclusions

This review provides a critical synthesis of digital twin developments in lithium-ion battery cell manufacturing, revealing that current approaches are predominantly focused on specific process steps such as slurry preparation, drying, calendaring, and cell assembly. While digital twins offer significant potential for process optimization, quality assurance, and data traceability, the analysis shows that most existing contributions remain fragmented and do not yet provide fully integrated representations of the complete manufacturing chain. Furthermore, although large volumes of process data are generated across battery production, challenges persist in data integration, interoperability, and traceability, limiting the ability to fully capture process–structure–performance relationships at the cell level.

The main contribution of this review lies in providing a structured and critical comparison of digital twin approaches across different scales and modelling strategies. By analyzing physics-based, data-driven, and system-level implementations in terms of maturity, scalability, and applicability, this work highlights key trade-offs between model fidelity and industrial deployment. In particular, the results demonstrate that high-fidelity models provide detailed physical insights but remain limited in scalability, while higher-maturity implementations prioritize integration and real-time applicability at the expense of physical resolution. In this context, data-driven and hybrid modelling approaches emerge as key enablers for bridging this gap, offering improved predictive capability and reduced experimental effort, although still constrained by data dependency and interpretability limitations.

Despite increasing interest in digital twins, the review highlights several critical limitations in the current state of the art, including the lack of standardization, limited quantitative validation, and insufficient integration across manufacturing stages. In addition, computational cost, data availability, and data governance challenges remain significant barriers to industrial deployment. Future research should therefore focus on developing multiscale and interoperable frameworks capable of linking process-level models with plant-level optimization, as well as establishing standardized validation methodologies and quantitative performance indicators. These needs are particularly critical in the context of gigafactory-scale manufacturing and emerging technologies such as solid-state and

sodium-ion batteries, where increased process complexity demands robust, scalable, and adaptable digital twin solutions.

Author Contributions: Methodology, M.G.-A. and V.F.-R.; Formal analysis, M.G.-A. and V.F.-R.; Writing—original draft, C.H.-P., J.d.L.-T. and V.O.-S.-C.; Writing—reviewing and editing, L.Z., A.L.-A., M.G.-A. and V.F.-R.; Supervision, M.G.-A. and V.F.-R. All authors have read and agreed to the published version of the manuscript.

Funding: TRACA “Trazabilidad y Circularidad Aplicada. Diseño y desarrollo de una solución de pasaporte digital de producto multisectorial para baterías y calzado”, IMDEEA/2025/49, is funded by the Valencian Institute for Business Competitiveness (IVACE+I) through an R&D agreement with the Generalitat Valenciana, within the framework of the 2025 call for Technological Centres to carry out R&D projects in collaboration with companies from the Valencian Community, with funding from the European Union through the European Regional Development Fund.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CATL	Contemporary Amperex Technology Co., Limited
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SoX	State of X
SEI	Solid Electrolyte Interphase
EOL	End of Line
EU	European Union
LMT	Light Means of Transport
kWh	Kilowatt-Hour
MES	Manufacturing Execution System
SCADA	Supervisory Control and Data Acquisition
OEE	Overall Equipment Effectiveness
AI	Artificial Intelligence
IoT	Internet of Things
ERP	Enterprise Resource Planning
CGDM	Coarse-Grained Molecular Dynamics
DEM	Discrete Element Model
LBM	Lattice Boltzmann Method

References

1. Yang, X.; Zhang, H.; Liu, Q.; Jiang, G. The Li-ion battery industry and its challenges. *Nat. Rev. Chem.* **2025**, *9*, 497–498. [[CrossRef](#)] [[PubMed](#)]
2. Attia, P.M.; Moch, E.; Herring, P.K. Challenges and opportunities for high-quality battery production at scale. *Nat. Commun.* **2025**, *16*, 611. [[CrossRef](#)] [[PubMed](#)]
3. Nekahi, A.; Feyzi, E.; Srivastava, M.; Yeganehdoust, F.; Madikere Raghunagtha Reddy, A.K.; Zaghib, K. Advanced lithium-ion battery process manufacturing equipment for gigafactories: Past, present, and future perspectives. *iScience* **2025**, *28*, 112691. [[CrossRef](#)] [[PubMed](#)]
4. du Baret de Limé, A.; Lein, T.; Maletti, S.; Schmal, K.; Reuber, S.; Heubner, C.; Michaelis, A. Impact of Electrode Defects on Battery Cell Performance: A Review. *Batter. Supercaps* **2022**, *5*, e202200239. [[CrossRef](#)]
5. European Parliament and Council of the European Union. Regulation (EU) 2023/1542 of the European Parliament and of the Council of 12 July 2023 concerning batteries and waste batteries, amending Directive 2008/98/EC and Regulation (EU) 2019/1020 and repealing Directive 2006/66/EC. *Off. J. Eur. Union* **2023**, *L191*, 1–117.

6. Soori, M.; Arezoo, B.; Dastres, R. Digital Twin for Smart Manufacturing: A Review. *Sustain. Manuf. Serv. Econ.* **2023**, *2*, 100017. [CrossRef]
7. Örum Aydın, A.; Zajonz, F.; Günther, T.; Dermenci, K.B.; Berecibar, M.; Urrutia, L. Lithium-Ion Battery Manufacturing: Industrial View on Processing Challenges, Possible Solutions and Recent Advances. *Batteries* **2023**, *9*, 555. [CrossRef]
8. Liu, Y.; Zhang, R.; Wang, J.; Wang, Y. Current and future lithium-ion battery manufacturing. *iScience* **2021**, *24*, 102332. [CrossRef] [PubMed]
9. PEM RWTH Aachen. VDMA. Lithium-Ion Battery Cell Production Process. Available online: https://www.pem.rwth-aachen.de/global/show_document.asp?id=aaaaaaaaabdqbt (accessed on 24 April 2026).
10. Arslan, K.K.; Dermenci, K.B.; Van Mierlo, J.; Berecibar, M. Current and future trends in lithium-ion battery electrode production machinery: A comprehensive review. *Appl. Energy* **2026**, *402*, 126968. [CrossRef]
11. Schomburg, F.; Heidrich, B.; Wennemar, S.; Drees, R.; Roth, T.; Kurat, M.; Heimes, H.; Jossen, A.; Winter, M.; Cheong, J.Y.; et al. Lithium-ion battery cell formation: Status and future directions towards a knowledge-based process design. *Energy Environ. Sci.* **2024**, *17*, 2686–2733. [CrossRef]
12. Kampker, A.; Heimes, H.H.; Dorn, B.; Clever, H.; Ludwigs, R.; Li, R.; Drescher, M. Concept for Digital Product Twins in Battery Cell Production. *World Electr. Veh. J.* **2023**, *14*, 108. [CrossRef]
13. Ventura Silva, G.; Thomitzek, M.; Lippke, M.; Heckmann, T.; Karaki, H.; Lischka, C.; Möhlen, F.; Mayer, D.; Hagemester, J.; Daub, R.; et al. Digitalization Platform for Sustainable Battery Cell Production: Coupling of Process, Production, and Product Models. *Energy Technol.* **2023**, *11*, 2200801. [CrossRef]
14. PEM RWTH Aachen; VDMA; Helmut Schmidt University. Data-Driven Production—Perspectives and Recommendations for Action Using the Example of Battery Cell Production. Available online: https://www.researchgate.net/publication/403170554_Data-Driven_Production_-_Perspectives_and_Recommendations_for_Action_Using_the_Example_of_Battery_Cell_Production (accessed on 19 May 2026).
15. Fraunhofer Research Institution for Battery Cell Production FFB. The Digital Twin in Battery Cell Production: Potential for Efficient and Sustainable Production. Münster, Germany, 2023. Available online: https://www.ffb.fraunhofer.de/content/dam/ipt/forschungsfertigung-batteriezeile/Dokumente/whitepaper/WhitePaper_FFB_Digitaler_Zwilling_EN_DOI.pdf (accessed on 19 May 2026).
16. Wanner, J.; Weeber, M.; Birke, K.P.; Sauer, A. Quality Modelling in Battery Cell Manufacturing Using Soft Sensing and Sensor Fusion—A Review. In *Proceedings of the 9th International Electric Drives Production Conference (EDPC), Esslingen, Germany, 3–4 December 2019*; IEEE: Piscataway, NJ, USA, 2019; pp. 1–9. [CrossRef]
17. Ayerbe, E.; Berecibar, M.; Clark, S.; Franco, A.A.; Ruhland, J. Digitalization of Battery Manufacturing: Current Status, Challenges, and Opportunities. *Adv. Energy Mater.* **2022**, *12*, 2102696. [CrossRef]
18. Manoharan, A.; Chong, J.J.; Choong, Z.J.; Lambert, S.; Gupta, R.K.; Chandra, D.; Jain, A.; Rao, A.; Sharma, A. Optimizing lithium-ion battery manufacturing with digitalization and AI-driven frameworks. *Int. J. Adv. Manuf. Technol.* **2026**, *142*, 1–37. [CrossRef]
19. Ludwigs, R.; Schmied, J.; Clever, H.; Heimes, H.; Kampker, A. Digital Twin in the Battery Production Context for the Realization of Industry 4.0 Applications. In *Proceedings of the Conference on Production Systems and Logistics (CPSL 2023)*; publish-Ing: Hannover, Germany, 2023. [CrossRef]
20. Gaines, L.; Zhang, J.; He, X.; Bouchard, J.; Melin, H.E. Tracking Flows of End-of-Life Battery Materials and Manufacturing Scrap. *Batteries* **2023**, *9*, 360. [CrossRef]
21. Hussein, K.; Schmidgruber, N.; Weinmann, H.W.; Maibaum, K.; Ruhland, J.; Fleischer, J. Development of a digital twin for improved ramp-up processes in the context of Li-ion-battery-cell-stack-formation. *Procedia CIRP* **2022**, *106*, 27–32. [CrossRef]
22. Degen, F.; Winter, M.; Bendig, D.; Tübke, J. Energy consumption of current and future production of lithium-ion and post lithium-ion battery cells. *Nat. Energy* **2023**, *8*, 1284–1295. [CrossRef]
23. Rubio-Rico, A.; Mengod-Bautista, F.; Lluna-Arriaga, A.; Arroyo-Torres, B.; Fuster-Roig, V. The industrial digital energy twin as a tool for the comprehensive optimization of industrial processes. *Processes* **2023**, *11*, 2353. [CrossRef]
24. Rubio-Rico, A.; Mengod-Bautista, F.; Ruiz-Perdomo, L.; Lluna-Arriaga, A.; Cutillas-Sánchez, P.; Fuster-Roig, V. Energy forecasting in digital twins: A comparative evaluation of various methods. *IFAC-PapersOnLine* **2025**, *59*, 1618–1623. [CrossRef]
25. Grieves, M.; Vickers, J. Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In *Transdisciplinary Perspectives on Complex Systems*; Kahlen, F.J., Flumerfelt, S., Alves, A., Eds.; Springer: Cham, Switzerland, 2017; pp. 85–113. [CrossRef]
26. Tao, F.; Cheng, J.; Qi, Q.; Zhang, M.; Zhang, H.; Sui, F. Digital twin-driven product design, manufacturing and service with big data. *Int. J. Adv. Manuf. Technol.* **2018**, *94*, 3563–3576. [CrossRef]
27. Kritzinger, W.; Karner, M.; Traar, G.; Henjes, J.; Sihn, W. Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine* **2018**, *51*, 1016–1022. [CrossRef]

28. Rubio Rico, A.; Lluna Arriaga, A.; Mengod Bautista, F.; Ruiz Pérdomo, L.E.; Cutillas Sánchez, P.J. GEDAI: El Gemelo Digital para la mejora de energía y agua residual de proceso. In Proceedings of the CONAMA 2024: Congreso Nacional del Medio Ambiente, Madrid, España, 2–5 December 2024.
29. Mengod-Bautista, F.; Rubio-Rico, A.; Ruiz-Perdomo, L.; Lluna-Arriaga, A.; Cutillas-Sánchez, P.; Fuster-Roig, V. Gemelo Digital Energético como motor de la eficiencia energética y sostenibilidad, su aplicación en sectores críticos productivos y su proyección a Defensa. In Proceedings of the XII Congreso Nacional de I+D en Defensa y Seguridad, Zamora, España, 11–13 November 2025.
30. Haghi, S.; Aykol, M.; Türeci, D.; Groß, T.; Mayr, A.; Lienkamp, M. Machine Learning in Lithium-Ion Battery Cell Production: A Comprehensive Mapping Study. *Batter. Supercaps* **2023**, *6*, e202300046. [[CrossRef](#)]
31. Naseri, F.; Gil, S.; Barbu, C.; Cetkin, E.; Yarmica, G.; Jensen, A.C.; Larsen, P.G.; Gomes, C. Digital twin of electric vehicle battery systems: Comprehensive review of the use cases, requirements, and platforms. *Renew. Sustain. Energy Rev.* **2023**, *179*, 113280. [[CrossRef](#)]
32. Lombardo, T.; Hoock, J.; Primo, E.N.; Ngandjong, A.C.; Duquesnoy, M.; Franco, A.A. Accelerated optimization methods for force-field parametrization in battery electrode manufacturing modeling. *Batter. Supercaps* **2020**, *3*, 721–730. [[CrossRef](#)]
33. Lombardo, T.; Ngandjong, A.C.; Belhcn, A.; Franco, A.A. Carbon-binder migration: A three-dimensional drying model for lithium-ion battery electrodes. *Energy Storage Mater.* **2021**, *43*, 337–347. [[CrossRef](#)]
34. Ngandjong, A.C.; Lombardo, T.; Primo, E.N.; Chouchane, M.; Shodiev, A.; Arcelus, O.; Franco, A.A. Investigating electrode calendering and its impact on electrochemical performance by means of a new discrete element method model: Towards a digital twin of Li-Ion battery manufacturing. *J. Power Sources* **2021**, *485*, 229320. [[CrossRef](#)]
35. Shodiev, A.; Primo, E.; Arcelus, O.; Chouchane, M.; Osenberg, M.; Hilger, A.; Manke, I.; Li, J.; Franco, A.A. Insight on electrolyte infiltration of lithium ion battery electrodes by means of a new three-dimensional-resolved lattice Boltzmann model. *Energy Storage Mater.* **2021**, *38*, 80–92. [[CrossRef](#)]
36. Shodiev, A.; Zanolto, F.M.; Yu, J.; Chouchane, M.; Li, J.; Franco, A.A. Designing electrode architectures to facilitate electrolyte infiltration for lithium-ion batteries. *Energy Storage Mater.* **2022**, *49*, 268–277. [[CrossRef](#)]
37. Shodiev, A.; Duquesnoy, M.; Arcelus, O.; Chouchane, M.; Li, J.; Franco, A.A. Machine learning 3D-resolved prediction of electrolyte infiltration in battery porous electrodes. *J. Power Sources* **2021**, *511*, 230384. [[CrossRef](#)]
38. Chouchane, M.; Rucci, A.; Lombardo, T.; Ngandjong, A.C.; Franco, A.A. Lithium ion battery electrodes predicted from manufacturing simulations: Assessing the impact of the carbon-binder spatial location on the electrochemical performance. *J. Power Sources* **2019**, *444*, 227285. [[CrossRef](#)]
39. Troncoso, J.F.; Zanolto, F.M.; Galvez-Aranda, D.E.; Zapata Dominguez, D.; Denisart, L.; Franco, A.A. The ARTISTIC Battery Manufacturing Digitalization Initiative: From Fundamental Research to Industrialization. *Batter. Supercaps* **2025**, *8*, e202400385. [[CrossRef](#)]
40. Henschel, S.; Otte, S.; Mayer, D.; Fleischer, J. Use cases for digital twins in battery cell manufacturing. In *Production at the Leading Edge of Technology*; Liewald, M., Ed.; Springer: Cham, Switzerland, 2023; pp. 833–842. [[CrossRef](#)]
41. Sharma, A.; Tiwari, M.K. Digital twin design and analytics for scaling up electric vehicle battery production using robots. *Int. J. Prod. Res.* **2023**, *61*, 8512–8546. [[CrossRef](#)]
42. Li, C.; Li, Z.; Ding, H.; Huang, J.; Zhang, H. Application of digital twin technology in production process optimization and performance prediction of new energy battery packs. *Appl. Math. Nonlinear Sci.* **2024**, *9*, 1–15. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.