The Power of Digitalization in Battery Cell Manufacturing

Whitepaper

Accenture Industry X

Executive Summary

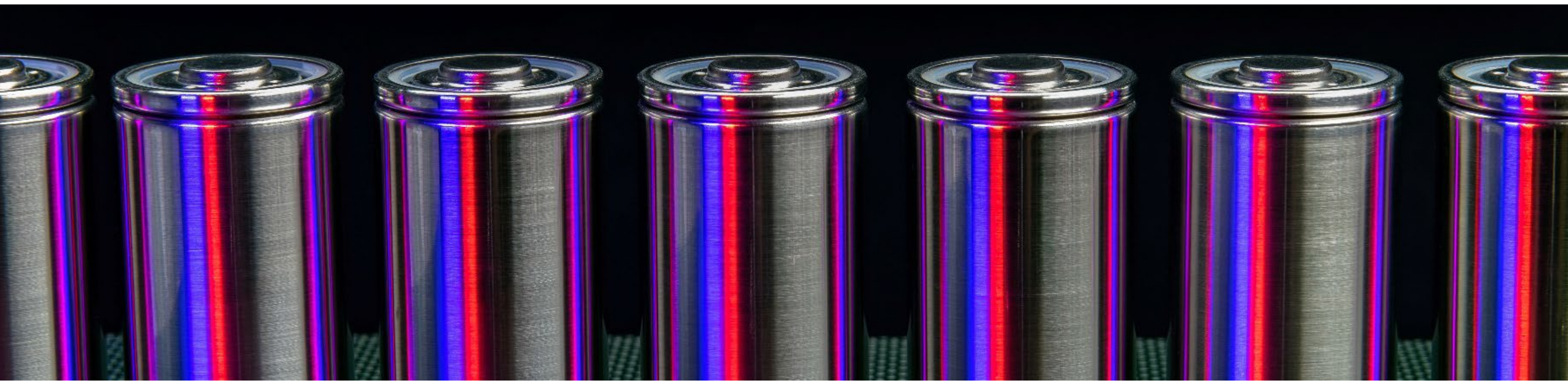
Digitalization plays a crucial role in mastering the challenges in battery cell production at scale. This Whitepaper provides an overview of digital enabling technologies and use cases, presents the outcomes of an industry expert survey, and illustrates the results of battery production cost modeling for a chosen set of seven high-impact use cases.

Battery and digitalization experts were invited to participate in an online survey aimed at gathering insights on how digital manufacturing solutions can enhance the primary cost drivers of battery cell production. The input is integrated into a Gigafactory model, which enables the quantification of cost and sustainability improvements when a cell manufacturer employs one of the use cases. The study results reveal that, in battery cell manufacturing, electrode production stands out as the primary beneficiary of digitalization, followed by cell finishing. The assembly process ranks third in terms of its potential for improvement through digitalization. The main production cost driver, as seen by the industry experts that participated in the survey, is above all the material scrap rate. The findings of the study quantify and affirm the many-faceted advantages of digitalization, including enhanced product yield, reduced machine downtimes, and increased energy efficiency.

Specific use cases of digitalization, covering different lifecycles of a plant, are analyzed in detail regarding their impact on the metrics in the field of operations, sustainably and costs. The data show that the implementation of predictive quality and traceability solutions stand out as the most effective levers to reduce battery material scrap rates by up to 10.3%, compared to a baseline scenario. Predictive maintenance allows to increase machine uptime by 7.2%, while energy management solutions can cut energy consumptions and related emissions by 9.3%. Simulation use cases with a virtual-first approach, such as digital production planning, virtual commissioning, and material flow modeling, contribute to de-bottleneck cell manufacturing operations and result in moderate production cost savings.

In a lithium-ion battery cell Gigafactory with annual production capacity of 40 GWh/a, the best investigated use cases offer roughly 0.8% reduction in cell production costs which translate into a potential annual saving of $30M. When considering the initial investment and operational costs for the digital solutions, all use cases result in a net positive cash flow after a few years in operation. Primarily software-based solutions demonstrate scalability and ease of implementation, whereas applications with greater hardware intensity demand closer scrutiny in terms of their payback period.

This study emphasizes that digitalization provides competitive advantages to battery cell manufacturers, but the costs and benefits of digital manufacturing use cases must be carefully analyzed and evaluated in terms of their economic advantage. The methodology outlined in this work aids cell manufacturers in making well-founded decisions, serving as a compass that directs the battery industry toward sustainable and impactful digital transformation roadmaps.



Key Findings

Electrode production takes center stage in digitalization efforts

Electrode production emerges as the primary beneficiary of digitalization efforts, with significant potential for improvements in scrap reduction, energy optimization, and maintenance efficiencies, resulting in a notable 0.8% cost reduction and a reduced environmental footprint.

Digital technologies drive down costs in battery cell manufacturing

The analysis identifies scrap rate as the predominant cost driver within battery cell manufacturing. Digital technologies, particularly predictive quality and traceability stand out due to their ability to substantially lower scrap rates by 6.1% and 10.3%, respectively, relative to a baseline figure. Predictive maintenance is also noted for its potential to decrease downtime by 7.2%.

Tracking and optimization drive sustainability gain

Energy tracking and optimization play a crucial role in advancing sustainability objectives, contributing to energy conservation with a potential reduction in energy usage and emissions by approximately 9.5%. This aligns with broader industry objectives for environmental responsibility and efficiency.

Virtual commissioning and traceability save $30M annually in cell manufacturing

The Whitepaper illustrates the economic benefits of digitalization, emphasizing cost reduction in material and manufacturing processes. Notably, virtual commissioning and traceability are marked for their highest potential in cell cost reduction, offering around 0.8% cost reduction or $30M annual saving in a typical Gigafactory.

A strategic approach can lead to the most value

The study provides strategic insights into the deployment of digital technologies, suggesting a prioritized approach based on the lifecycle stage of the manufacturing plant. Software-based solutions are recommended for their scalability and lower initial investment, while more complex hardware-intensive applications warrant cautious financial consideration but could add the most value in the long run.

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Introduction

The demand for batteries is experiencing rapid growth as major industrial nations advance in their efforts to achieve decarbonization in the mobility and energy sectors. By the year 2025, the global installed battery production capacity is expected to reach around 4 terawatt-hours per year (TWh/a) and may exceed 6.5 TWh/a in 2030 [1]. These figures indicate that there will be significant and dynamic growth in the battery industry. In response to this trend, companies are addressing the demand by establishing gigawatt-scale battery cell production facilities, 'Gigafactories' in Asia, Europe, North America, India and South-East Asia.

The infrastructure project boom in this sector brings forth a distinct set of challenges. Among those challenges are (i) achieving the highest production efficiency given a constrained supply of critical raw materials [2], (ii) dealing with the technical complexity of the battery cell production processes, and (iii) reaching economic scale to make the production viable. In the latter half of this decade, we will witness the global ramp-up of battery manufacturing plants, marking a crucial period for the industrialization of modern battery cell technology. This is accompanied by fierce global competition for the best technologies, regional funds and investments, and production expertise. Smart manufacturing solutions emerge as a modern approach to master the intricacies of large-scale, highly complex battery cell production [3]. Enabled by digital technologies and data-driven methodologies, cell manufacturers attempt to make their batteries cheaper and more sustainable. The potential of digitalization in the context of modern lithium-ion battery cell production is the main subject of investigation in this Whitepaper. With this study, we seek to assess whether the implementation of digital technologies will give market participants a competitive edge. Therefore, we initiated an expert survey to gather industry insights in the first step, and then quantify the economic benefits with a comprehensive battery cell manufacturing cost model in the second step.

We present and discuss a variety of enabling technologies and digital use cases for the 'battery factory of the future'. To stay focused on the realization of value for Gigafactories, rather than visionary concepts and buzzwords, a shortlisted selection of digital use cases is presented to the participants of the industry survey, who were asked to evaluate the effects on key performance indicators (KPIs) in battery production. The collaborative efforts with experts yield noteworthy outcomes, underlining the need for a baseline scenario that allows to quantify the impact of new manufacturing solutions. The aggregated data are used to run cost calculations for a state-of-the-art Gigafactory business case and investigate the digital technology impact on operational, sustainability and cost metrics. The discoveries in this study help cell manufacturers to prioritize the right digital technologies and use cases, and the results provide guidance for strategic decision making in the digital transformation process.

Digital Battery Cell Manufacturing – A Macro Analysis

Digital Manufacturing

In an era of rapid technological advancement, digitalization has emerged as a catalyst for transformative change in production. This chapter starts with an introduction of **five general advantages** that digitalization brings to manufacturing processes.

1. Process optimization

Digitalization enables the live monitoring, control and even adaption of processes for nearly all stages of production. Through interconnected systems, manufacturers can identify bottlenecks, streamline workflows, and shift resources towards a more effective allocation. This reduces production cycle times, saves costs, and especially enhances the overall equipment effectiveness (OEE), a commonly used metric in manufacturing to measure the efficiency of a production process, measured by factors such as equipment availability, performance, and quality of the produced parts.

2. Data-driven decision making

The integration of digital technologies provides manufacturers with comprehensive data streams from the shopfloor to the 'top floor' (enterprise-level), plus several new options on how to generate value out of that data. Advanced analytics and machine learning algorithms can be used to process manufacturing data in order to gain insights that support automatic decision-making. Data-driven insights enhance accuracy, minimize downtime, and contribute to a continuous improvement of the manufacturing processes from the prediction of maintenance needs to the streamlining of material flows.

3. Agile resilience

Digitalization promotes adaptive manufacturing, which allows manufacturers to swiftly respond to changing customer demands and or disruptive events in the company or on the shopfloor. Data-enabled insights facilitate high responsiveness and fast adjustments in production schedules and can potentially minimize the detrimental impact of unforeseen events. This flexibility is crucial especially in dynamic markets where demand and supply patterns and regulatory requirements can change rapidly, and a producer must be able to react quickly.

4. Enhanced traceability

Digitalization enables end-to-end traceability of components and processes within a manufacturing plant through track-and-trace hardware and software solutions. Manufacturers can follow the origin of materials in real time, monitor the material flow in all production stages simultaneously, and ensure compliance with quality standards and regulations. Both upstream and downstream traceability play crucial roles for industrial supply chains beyond battery cell manufacturing in ensuring transparency and accountability.

5. Product optimization

Based on in-line measurements and traceability it becomes possible for systems or processes to accurately monitor and forecast the outcome or performance of manufactured products. This involves utilizing data analysis, data-driven models, and algorithms to detect or anticipate potential product defects, deviations from quality specifications, or inefficiencies in the production process. By harnessing digital analytics, manufacturers can proactively address issues, adapt the product design for better manufacturability, optimize production parameters, and ultimately enhance the overall quality of their products.

The integration of digital and smart manufacturing solutions is often heralded as a transformative force. However, a lack of understanding about its applications and benefits can hinder its adoption and, consequently, a manufacturer's ability to become or stay successful in an increasingly complex manufacturing environment. The following section describes frequently overlooked aspects of digitalization – challenges, pitfalls and lessons learned about digital manufacturing from other industries.

Neglecting the holistic approach

The full potential of digitalization cannot be achieved with fragmented solutions only. A comprehensive digital strategy is required in order to select, implement and manage suitable solutions. While it is essential to digitize and automate certain processes, this is just one step of the first steps to become a fully digital enterprise. Thoughtfully crafted solution architectures cover the entire spectrum, spanning from the sourcing of raw materials to the finished goods. In the digital end-to-end world, the interoperability of IT systems and the seamless flow of information is as critical as the physical material flow between machines on the shopfloor. This requires careful planning from data acquisition and processing to resilient functionality of software suites in changing production environments. For established companies, the digital transformation journey might begin with retrospective digitization of existing information, which mainly involves converting analog information into digital format, while startups and new ventures enter the market as digital natives, who can more easily navigate in a fully digital environment. Digitalization is not a singular measure; instead, it can be implemented through diverse applications, referred to as use cases. A narrow perspective that sees digitalization as pure conversion of the analog world into digital world and automation alone misses out on the benefits that the broader picture has to offer [5].

Underestimating the power of well-organized data

Some manufacturers may view data collection as an ancillary task, rather than a fundamental building block of a modern factory. Failing to embrace this mindset leads to a missed opportunity to leverage the power of data-driven decision-making, as data serves as the backbone of digitalization and is a valuable asset. On the other end of the spectrum, unorganized and blind data collection will not make companies 'data-rich' but rather 'data-obese', which will lead to unnecessary complexity and cost. Only by collecting, analyzing, and interpreting an appropriate amount of high-quality data, manufacturers gain deep insights into their manufacturing processes and can make informed decisions. Predictive maintenance, performance optimization, and adaptive manufacturing are just a few examples of the ways data can be leveraged to drive efficiency and innovation in battery production and enables new business models [6].

Dismissing scalability and accessibility

Some might still believe that digitalization is an exclusive privilege of large corporations with substantial financial resources and a worldclass IT department. Today, digital technology has become increasingly accessible and affordable for businesses of all sizes. Digital enterprise and manufacturing solutions are scalable, meaning they can be tailored to suit the specific needs and budgets of different manufacturers. Often, solutions are transferrable, facilitating platform interoperability between processes and industries [5].

Neglecting industry-specific applications battery production is a unique field with specific requirements and challenges. Failing to recognize the adaptability of digitalization to these specific needs can result in missing out of the full potential. Software solutions can be customized to address the complexities of battery production, offering solutions that enhance traceability, quality control, production efficiency and sustainability at the same time [5].

Battery Cell Manufacturing

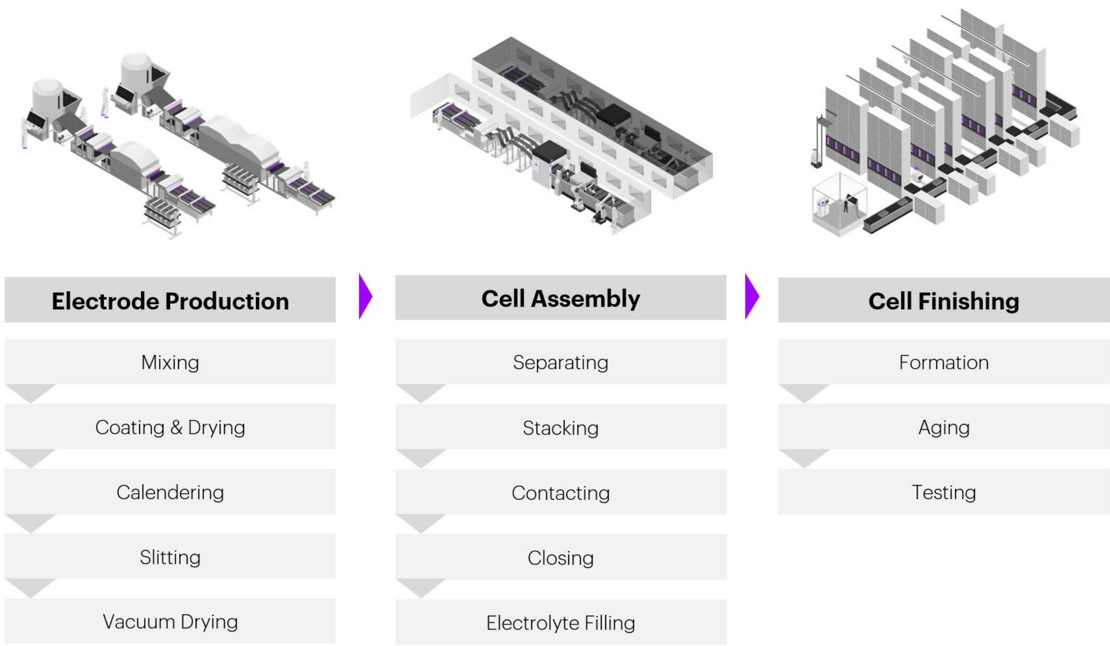


Figure 1: The conventional production of the lithium-ion battery cell (pouch type) consists usually of three main process steps, electrode manufacturing, cell assembly and cell finishing.

To uncover and evaluate digitalization potentials, a more detailed look at battery cell production is therefore necessary. This chapter provides an overview of the fundamentals of battery cell manufacturing and some key cost drivers of the product.

Figure 1 shows that the simplified production process of contemporary intercalation-type battery cells, like lithium- or sodium-ion batteries, is split into three main process segments. The first main segment is the production of electrodes. Battery active material powders and various processing chemicals are mixed and then coated on current collector foils. The electrodes are dried, calendared, slitted and eventually dried again under vacuum. Afterwards the cells are assembled via separation (singulation), stacking and contacting of the electrodes. These electrode sheet bundles are enclosed, and the electrolyte is filled in. After the cells are assembled, they are electrochemically activated through a formation and aging procedure and finally tested at the end of the line [7]. Though there are several technology roadmaps with manufacturing process variations and innovations for modern battery production plants (e.g., dry coating, pre-lithiation, baking just before electrolyte filling) we will refer to this generic process flow throughout this paper for the sake of simplicity and cost modelling.

To quantify the benefits that can be realized with certain digital solutions, the battery production cost will be used as the main factor, and we will investigate a sub-set of cost drivers as key performance indicators (KPIs).

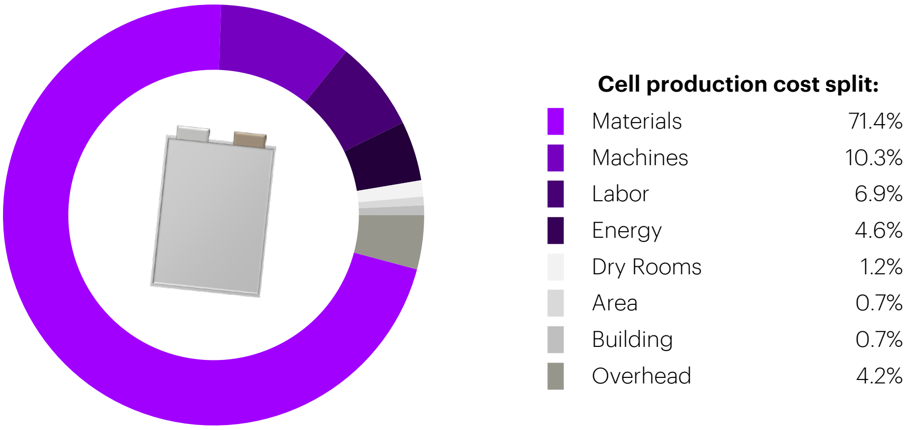


Figure 2: Cost breakdown of a battery cell, Fraunhofer FFB calculation based on a NMC811-graphite 52 Ah pouch cell in a 40 GWh/a production plant.

Figure 2 illustrates the production cost breakdown for a typical lithium-ion battery cell. More than 90% of the total battery cell production costs can be attributed to the following four main cost drivers:

Materials

Battery materials make up for the largest share of the battery cell production cost, roughly over 70% for the selected NMC-graphite chemistry. Depending on the cell design and the material prices this share can fluctuate between 65-77% [11]. Efforts should be made to minimize material usage, particularly by reducing the number of products that must be discarded due to quality issues. This scrap rate, which represents the number of materials or intermediate parts that fail to meet quality specifications, can have a substantial impact on costs. Therefore, reducing the scrap rate is crucial to cost optimization. Waste can be minimized through product and process design for circularity, stable and efficient processes or direct reuse or recycling of certain battery components [7]. The scrap rate will be used as one of the central quantitative KPIs to be investigated. Mitigating the impact of this cost driver is essential for battery cell manufacturers because the scrap rate can quickly vary between 2% to 25%. This depends on complex interactions between manufacturing parameters, the customer (e.g., automotive Original Equipment Manufacturer, OEM) expectations or the ramp-up management of production campaigns when introducing new products. We assume a scrap rate of 11.7%, cumulated over all manufacturing process steps, as baseline for the production cost modelling.

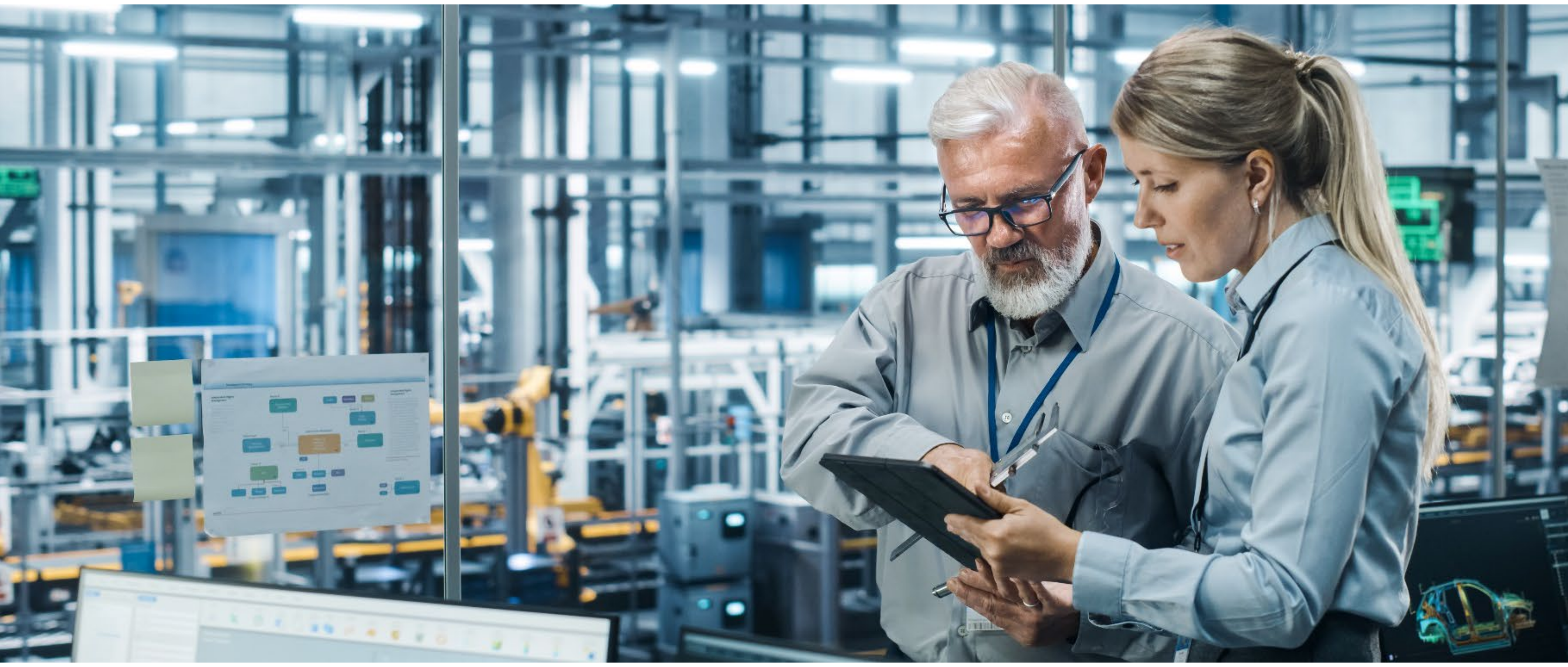
Machines

The efficient utilization of machinery is essential in controlling costs, since the machine depreciation and associated operation expenses are the second largest cost share with approximately 10% contribution to total cost [10]. The main machine cost driver is the large capital expenditure (CAPEX), which are typically in the range of multiple million Euros per production line (per GWh production capacity). Downtime, the time periods when machines are not in operation, e.g., due to planned maintenance or forced shutdowns, will result in less productive time, and increased costs. Maximizing machine uptime through measures like preventive maintenance and efficient scheduling can significantly impact the cost structure. Hence, we will use maintenance and downtime with a baseline value of 15% as the second KPI that is being assessed in the expert survey.

Labor
The number of staff needed for various tasks, their skill levels, and the related labor costs contribute to approximately 7% of overall production expenses. Balancing the workforce and optimizing the level of automation to reduce labor costs while maintaining product quality is a key consideration in cost management [8]. While the reduction of the required number of human operators is traditionally associated with hardware and process automation, digital solutions and software can also contribute to save labor costs. In the cost model we calculate with a baseline headcount of 2,685 employees in a 40 GWh/a production plant.

Energy
Energy consumption represents another crucial factor influencing the overall cost of battery cells, accounting for nearly 5%. Battery manufacturing requires around 30-55 kWh energy input for one kWh of produced cell as output [9]. The baseline assumption for this study is 46.7 kWh per kWh of produced battery cells. Especially electrode drying through convection ovens and the operation of dry and clean rooms are the most energy-intensive steps. Optimizing the KPI 'energy consumption' in battery cell production can lead to significant cost savings. Implementing energy-efficient technologies and practices can help reduce the overall cost of production [9].

Note that labor and energy cost are heavily dependent on the location of the battery manufacturing plant. While these costs are particularly high in Western European countries, their cost share differs for Eastern Europe or Asia. Furthermore, the exemplary battery cost breakdown as shown in Figure 2 includes additional minor cost drivers such as cost per square meter of production area, building and infrastructure investment and operational cost, dry room operation costs and various overhead expenses. For the sake of modelling simplicity and limited survey complexity, these factors are disregarded in our calculations.



Digital Technologies

Battery cell manufacturing can be divided into the physical or the digital space, as shown in Figure 3. The purpose of this illustration is to offer a foundational understanding of technical terminology. In battery cell manufacturing, the convergence of the digital space and the physical space is going to revolutionize the industry, enabling enhanced efficiency, productivity, and quality. This chapter elaborates the interplay between these two spaces, focusing on use cases, digital twins, enabling technologies, and their impact on the shopfloor.

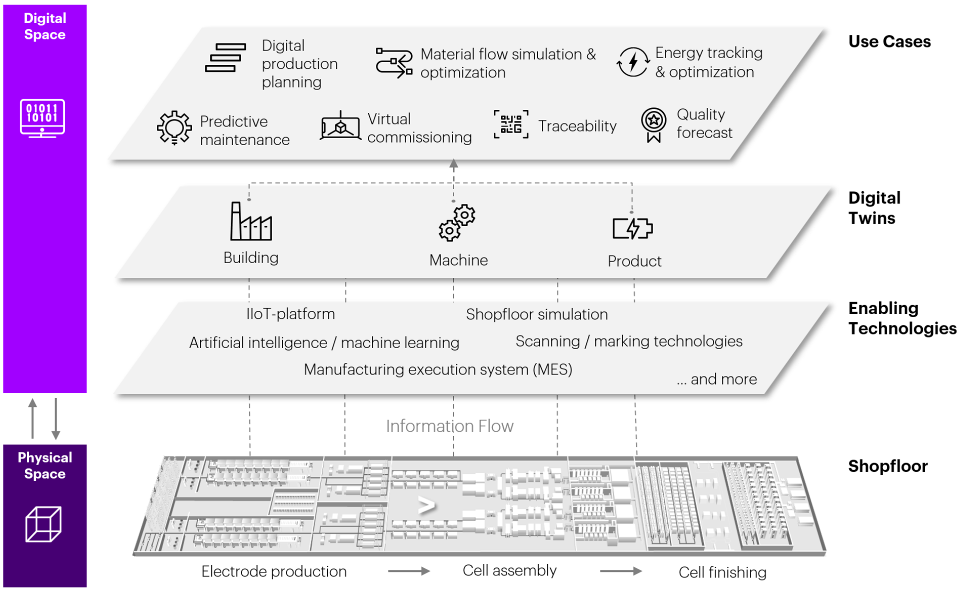


Figure 3: Layers and interdependencies of the physical and digital space

The physical space comprises all assets on the shopfloor. It includes the machines used in electrode production, cell assembly, and cell finishing as well as intermediary products such as electrode sheets. A bi-directional information flow connects the physical and the digital space. The digital space of a factory consists of three layers: enabling technologies, digital twins, and the use cases that can be built on top.

Enabling technologies are a diverse array of tools and systems to connect the digital space with the shopfloor and allow to collect, store, process and analyze data. These technologies, such as the industrial internet of things (IIoT) or artificial intelligence (AI), are the foundation for transformative changes through digitalization. In this Whitepaper, we only provide a high-level overview digital enabling technologies for battery cell manufacturing.

The second layer of the digital space consists of **digital twins (DTs),** which are digital representations of real-world objects. We differentiate between digital representations of buildings, machines, and products, using the term 'digital twin' to encompass any form of digital model, shadow, or digital representation, without strict requirements on features like real-time bi-directional data flow. A DT acts as a data foundation in entire digital space. It will allow to implement digital solutions use cases across the entire organization and enable satisfactory return on investment and real competitive advantages.

DTs harness enabling technologies to facilitate the realization of the third layer, enabling the implementation of digitalization **use cases**. For example, a digital machine twin may use its IIoT platform-enabled data connection and AI to implement a predictive maintenance use case [4][3]. Being the central focus of our model-based investigation, specific use cases will be thoroughly examined in detail.

Enabling Technologies

In the era of digitalization, new advanced technologies are transforming the production landscape. Table 1 shows a list of key hardware and software innovations that enable the transition to digital production. This chapter navigates through some of the key technologies and their associated impact on production, presenting a curated selection of the most relevant and popular advancements in the field. As stated in the previous section, we distinguish between enabling technologies and use cases.

The enabling technologies are specific digital or cyber-physical (often: 'Industry 4.0') technologies that allow for the realization of use cases like traceability or quality forecasting. As information technology (IT) and operational technology (OT) are converging, the enabling technologies can be a mix of hardware and software solutions.

Table 1: List of enabling technologies.

Software	Simulation	Connectivity
ERP	BIM & 3D models	Edge / cloud computing
MES	Process modelling & simulation	5G
PLM	CFD simulation programs	Edge devices
LIMS	Advanced planning / scheduling	Connected worker
KPI dashboards	Information models	**IIoT platform**
SCADA	**Shopfloor simulation**	OPC UA CS
QMS	AR / VR	Ontologies
Building automation	Modeling software (e.g. CAD)	Retrofitting
Smart learning platform		

Hardware	Data Handling	Product
Scanning / marking	Data Lake	DPP
Computer vision	**AI / ML**	RGM
HMI	Historian	DT-implementation platform
Camera system	DBMS	
GPUs	Parameter list	
Smart / soft sensors		
Robotics & AGVs		

To some extent most of these enablers are likely to be found in a modern battery cell production plant [3]. Table 2 shows a more detailed description of some highly relevant or especially popular solutions. Modern manufacturers have ambitions to complement existing manufacturing applications (e.g., MES) with a 'system of intelligence' to further drive improvements and value creation by combining data from shopfloor with enterprise data. This typically comprises a platform-based approach with modular apps with dedicated business context. Technologies like this help a company to anticipate events, link them to the applications of interest and enable real-time reactions based on data.

Table 2: Selected digital enabling technologies are accompanied by descriptions explaining their nature and detailing their impact on modern manufacturing

Technology	Description	Impact Estimation
IIoT-Platform	The Industrial Internet of Things (IIoT) Platforms are software solutions designed to streamline the configuration, administration, and utilization of connected devices in industrial environments. They enable Industry 4.0 approaches for easy communication, data collection, analysis, and control of devices in the factory network remotely [3].	IIoT platforms offer features such as data aggregation, real-time monitoring, remote management, and interoperability between different devices and systems. By leveraging IIoT platforms, cell manufacturers can respond to the requirements of processes with varying degrees of data intensity (e.g., sealing vs. data-heavy formation). Thus, gaining actionable insights from the vast amount of data generated by connected industrial assets.
Scanning/ Marking Technologies	Scanning and marking technologies capture digital replications of physical objects or documents using sensors, cameras, lasers, or other digitizing technologies. They allow to create accurate digital models to link the collected production data with (individual) products. Marking technologies typically work with patterns, codes, text, or images on surfaces [14].	Scanners and markers enable precise measurements, quality control, 3D modelling, and documentation of real-world objects for analysis, replication, or visualization. These technologies help to link process data with intermediate parts and the final product, the battery cell. Based on this, full forward and backward traceability can be achieved, which is the basis for the implementation of predictive quality for all intermediate and the final product.
Robotics & AGVs	Robots are utilized for tasks such as assembly, handling, and inspection. Automated Guided Vehicles (AGVs) autonomously transport materials and components within the production facility, ensuring a seamless and automated flow of resources.	Robotic solutions are used for automatic transportation of intermediate parts or the handling of battery cells during assembly and formation. Robots and AGVs contribute to increased productivity since processes are fully automated. Also, they reduce the risks of human error and hence improve scrap rates, and safety levels. Overall, manufacturing efficiency and precision can be enhanced with autonomous intralogistics solutions [3].
Shopfloor Simulation	Shopfloor simulation involves modeling the behavior of complex systems that evolve discretely over time. In this context, systems are depicted as sequences of events, where each event modifies the system's state and triggers subsequent events. The simulation models consider all relevant manufacturing assets such as machines, workstations, materials, and operator-machine-interfaces to replicate real-world behavior and interactions in an operational setting [3].	Shopfloor simulation enables analysts to evaluate different scenarios, optimize processes, and make informed decisions. Simulations are helpful especially for complex manufacturing such as battery cell production that is known for its many interdependent process steps and parameters. Plant simulation allows users to experiment with different layouts, scheduling strategies, resource allocations, and production scenarios, detect and alleviate the impact of bottlenecks, and ultimately also improve the overall plant efficiency.
Manufacturing Execution System (MES)	A Manufacturing Execution System (MES) is a software that connects enterprise-level systems like ERPs with the manufacturing shopfloor. It monitors and controls operations in real time, orchestrates and streamlines production sequences, resource allocation, data collection, and quality checks [3].	MES aims to optimize production workflows, enable digital insights into manufacturing operations, and improve the overall operational efficiency. This is especially challenging in battery cell manufacturing as the process steps greatly differ from each other – e.g. through the shift from continuous powder processing to discrete part manufacturing. A versatile MES can ensure accurate data exchange for decision-making across continuous electrode paste extrusion, roll-to-roll processing as well as stack assembly and electro-chemical process steps.
Artificial Intelligence/ Machine Learning	Artificial Intelligence (AI) includes subfields like machine learning (ML), which use algorithms to let computers learn from data, find patterns, and make predictions. AI can replicate human-like intelligence in machines. It involves algorithms, software, and hardware enabling computers to do tasks such as understanding language, recognizing patterns, making decisions, problem-solving, and learning [3].	ML has applications in various fields from lab-scale to mass manufacturing in industrial plants [12]. Predictive algorithms enhance quality control, identify potential defects early on, and optimize production parameters for improved efficiency. This can help in reducing customer dissatisfaction, costly warranty returns, and loss of corporate reputation. One exemplary application is predictive maintenance, which anticipates equipment failure before it occurs, allowing to minimize downtime and increase productivity [13].

Use Case Clusters

Having introduced the enabling technologies in the previous section, we now transition to the examination of use cases, which constitute the primary subject of investigation in this study. The most relevant digitalization use cases were identified as part of a joint project kick-off workshop held by Accenture and the Fraunhofer FFB. A total of 39 use cases were identified and clustered according to their areas of impact to allow for a more structured analysis. Organizing use cases based on the clusters where they exert the most significant impact facilitates a more focused approach for implementing digital solutions across diverse operational areas. These are the five categories:

Product
Product data collected during production and the entire lifetime of a battery contributes to improving the product development process, the product quality, and its manufacturability.

Machine
Manufacturing machines are the most important gateway to collecting process data along the battery cell production line. Built-in PLCs (Programmable Logic Controllers) execute data-driven decisions. Digitalization facilitates the mitigation of the impact of downtimes and setup times, leading to an increase in machine utilization.

Production process
Digitalization-enabled data collection along the production process will reveal hidden product-production relations across processes. These findings will be used for process parameter optimization and early quality predictions. Thus, decreasing scrap and improving cell quality.

Building
Gathering building and infrastructure information and creating a digital representation of a production plants unlocks various advantages. Use cases within this cluster contribute to optimize the factory layout or the energy consumption and therefore both the architectural and ecological footprint of the building.

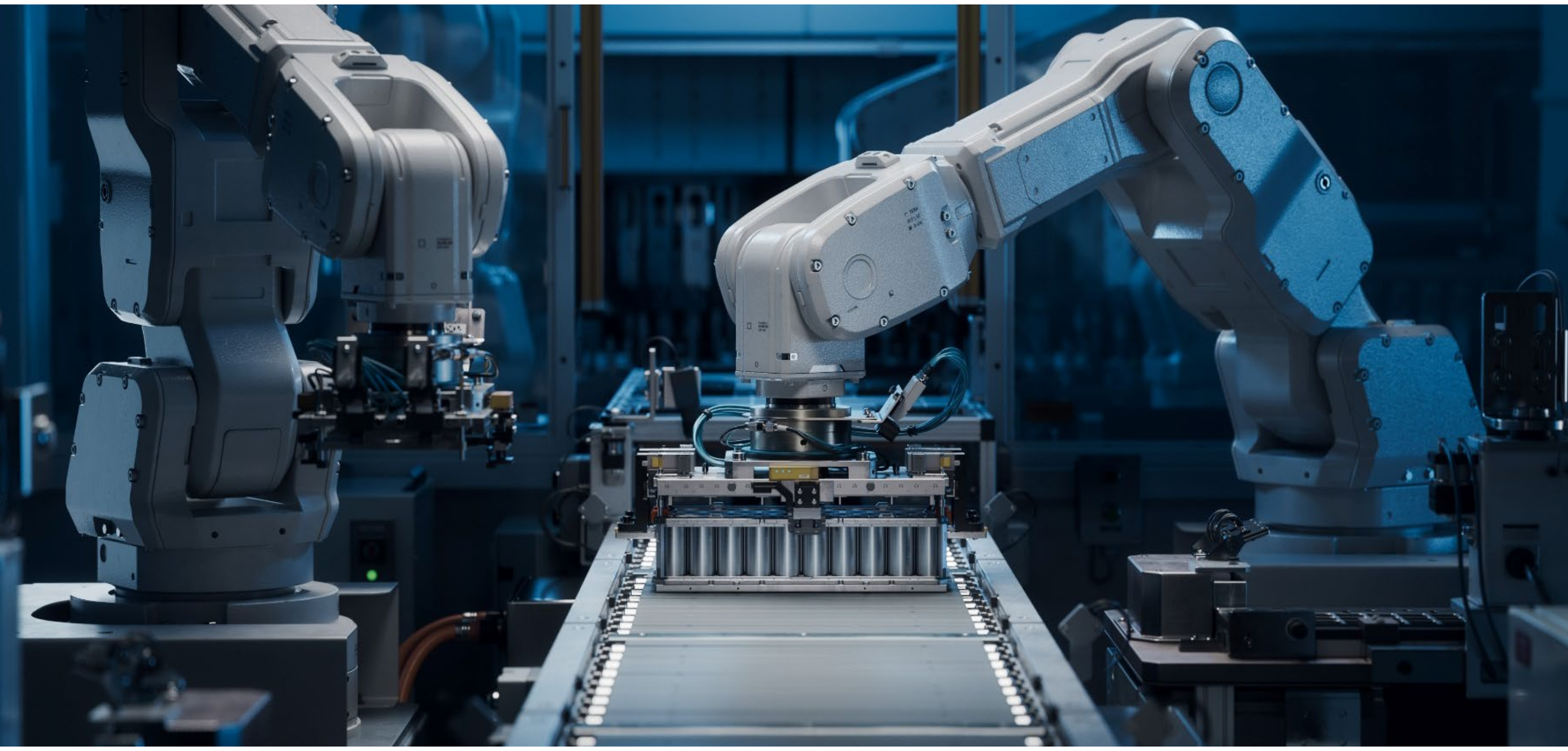
Production planning
Smooth and efficient production depends on organized planning. Digital scheduling, planning, and route optimization are essential digital tools that form the foundation for planning a factory before its ramp-up and optimizing its operational performance.

All use cases were qualitatively discussed by the project team and sorted according to their potential relevance and applicability in battery cell production, and various other factors such as technology readiness. A choice of seven promising use cases has been curated, ensuring at least one-use case per cluster and relevance across different stages of a battery manufacturing plant lifecycle – from production planning to the late-stage optimization of operations. The shortlisted seven use cases, highlighted in Table 3, ended up being featured in the expert survey and were put into the spotlight for a deeper analysis in this work. While use cases such as supply chain and sustainability are important aspects to consider, it is important to note that this report focuses on production relates use cases. The remaining options will not be extensively covered in this study, but they certainly merit further investigation.

Table 3: Clustered list of considered use cases. The use cases marked in bold are the selected subjects of investigation in this study

Machine	Product	Production Planning
Machine monitoring	Battery grading	Optimization of set-up times
Virtual commissioning	Evaluation 2^{nd} life applicability	**Digital production planning**
Predictive maintenance	Evaluation of recyclability	Digital scheduling of production
	Data-based performance optimization	AR/VR in production
	Predictive quality forecasting	
	Traceability	
	Battery passport	
	Battery cell simulation	

Building	Production Process/Control	Others
3D virtual shopfloor tour	Clustering of quality relevant parameters	Data-as-a-product
Layout optimization shopfloor	Cause-effect relationships	Network & business ecosystem analysis
Energy consumption forecast	Analysis & optimization across processes	Commodity price reduction
Automated warehousing	Adaptive production	Paperless workflow
Surveillance	CFD simulation	Product demand prediction
Route optimization	Quality gate	Supply chain monitoring
Energy tracking & optimization	Automation of manual processes	Customer management
	Material flow simulation & optimization	Technology life cycle analysis
		Distribution optimization



Industry Expert Survey

Survey Design and Results

The industry survey sets out to assess the impact of digitalization on key production metrics in battery cell production. Input was gathered from up to 145 individual contributors, of which a group of 63 participated in the expert study. All 63 provided their input to a light version of the survey, 43 completed the full technical scope including the use case evaluation, and 6 were confident enough to provide qualified input for all seven use cases on manufacturing process level. Participant background information was collected for the group of 63, who were invited to the study because of their expertise in digitalization or battery cell production, or both. The participants were asked about their years of professional experience in these fields. Two thirds of respondents stated one to three years of experience in battery production or more than three years in the field of digitalization (see Appendix Figure 10).
These experts are currently working for battery cell manufacturers, IT companies, and consulting and engineering companies. Most participants work for European or American companies, which is not fully representative for a global view on lithium-ion battery cell manufacturing. However, their mixed battery and digitalization perspectives ensure that the provided inputs are substantial and based on practical industry knowledge.

More than half of the participants rank electrode production as the most important area, where digitalization has a beneficial impact. The second-highest potential is seen in cell finishing, while cell assembly is ranked third for potential improvement by digitalization.

According to the industry consensus among battery producers, technical and scientific publications, and our views, the three segments can be described with the following key characteristics: electrode production is known for continuous processing of powdered chemicals, roll-to-roll handling, energy-intensive electrode drying and a low tolerance when it comes to inhomogeneity or impurities of the coated electrodes. Cell assembly comprises discrete high-speed and high-precision mechanical handling of electrode foils and intricate steps such as electrolyte filling, which is heavily affected by intermediate part properties. Cell finishing requires a sophisticated and product-specific electrochemical activation (formation) protocol, precise electrical process control and stable temperature conditions, which result in the formation and aging equipment being known to be especially CAPEX- and energy-intensive.

In their expert assessment, the participants recognized the key characteristics of the three process areas, the difficulty to control the respective manufacturing process steps and the complexity of the (intermediate) parts produced. A higher place in the ranking can also be interpreted as a greater overall optimization potential that lies within these areas if the typical challenges can be addressed or solved through digital technologies.

The four primary KPIs that drive the battery production cost (energy consumption, maintenance and downtime, scrap rate and required staff) are also ranked by the experts and the results are shown in Figure 4.

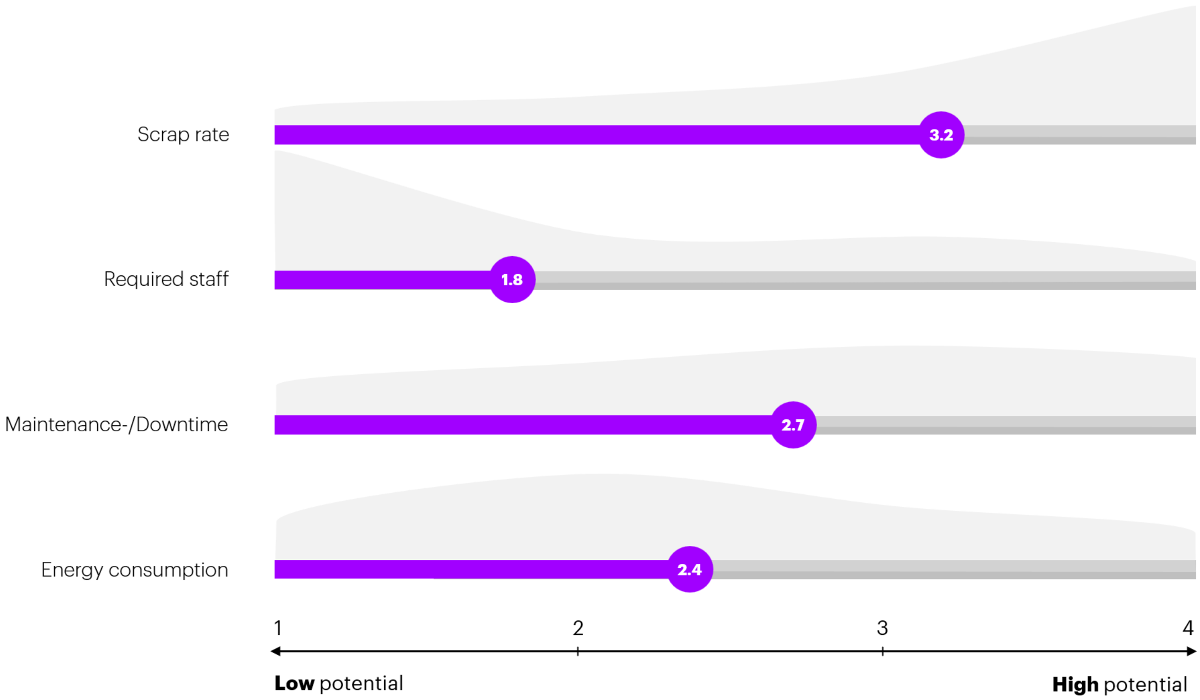


Figure 4: Expert ranking of cost driver impact. The survey participants (n = 63) were asked to rank the four main KPIs according to their potential benefit by digitalization.

The participants of the battery expert survey see above all the scrap rate as the biggest beneficiary of digitalization followed by downtime reduction and improvement potential to reduce the energy consumption. The least impact is expected for the reduction of required staff. This trend roughly represents the order in which the cost drivers appear on the in Figure 2: materials (71.4%) > machines (10.3%) > labor (6.9%) > energy (4.6%).

This indicates that the experts' primary concerns are to reduce the costly materials needed for battery cell production and ensuring uninterrupted manufacturing processes. An exemplary cost breakdown was not shown in the online survey, but it is generally known that production scrap is among the most significant cost drivers in battery cell production and that product quality can hardly be controlled without process automation and in-line measurements. Digital technologies are not credited with reducing the number of employees required to produce battery cells. However, we suggest that cell manufacturers should pay special attention to this point, because their staffing needs may change depending on the complexity and maintenance requirements of their digital enterprise and manufacturing solution architecture.

The provided bubble chart Figure 5 reflects the core results of the conducted survey. It offers a visual representation of the impact that the selected set of use cases (UCs) have on the presented metrics within a battery manufacturing process, focusing on electrode production, cell assembly, and cell finishing. Each bubble represents the mean of impact, with larger bubbles indicating a greater effect.

Figure 5: In an online survey, 63 participants were tasked with evaluating the impact of seven selected use cases on key performance indicators (KPIs) related to cost drivers. Participants expressed their input as a relative improvement compared to a baseline scenario for all cell manufacturing steps, spanning from mixing to end-of-life (EOL) cell testing. The mean results based on process step input are presented aggregated into the three main segments of cell production: electrode production, cell assembly, and cell finishing.

In electrode production, there is a notable cluster of large bubbles, suggesting that this stage could see significant KPI improvements, particularly in terms of maintenance and downtime, by implementing predictive maintenance and traceability. Regarding energy consumption, the chart implies that certain use cases, such as energy tracking and optimization, have the potential to reduce energy usage in electrode production by an estimated 11.2%. Conversely, in the cell assembly stage, this use case does not show a substantial opportunity for energy savings.

For maintenance and downtime, the implementation of predictive maintenance shows a promising potential reduction in downtime, particularly in electrode production, where a mean of 10.5% decrease is anticipated by the survey participants. When it comes to scrap rate, traceability shows the most significant impact, especially in the electrode production stage, where a 9.4% reduction in scrap rate is indicated. The impact on staffing requirements appears to be the least impactful among the metrics analyzed, as illustrated by the smaller bubbles in the chart.

However, there is still a notable influence, with the biggest impact being a 6.4% change in electrode production due to material flow simulation and optimization.

In the complete version of the survey, the selected group industry experts were asked to assess the impact on the four primary KPIs for each cell manufacturing step. Even for this group it proves to be challenging to specify the quantitative KPI improvements for each process step from mixing to EOL cell testing. Yet, that kind of process-level input is necessary for the sensitivity analysis with the cost model used in this study. The full results are shown in the Appendix Figure 11 and 12 for all uses cases and will be featured as one-by-one and side-by-side discussions in the upcoming chapters.

Survey Data Analysis

The data gathered in the expert survey are used to derive parameters for battery production modelling using a bottom up Gigafactory model. A state-of-the-art cell production scenario is used as the baseline to investigate the use cases' operational, economic, and ecological impact on battery production. The production scenario and baseline assumptions used are shown in Table 4.

Table 4: Production scenario and assumptions

Production Scenario	
Production Capacity	40 GWh/a
Cell Format	Pouch
Cell Chemistry	NMC 811 - Graphite
Cell Capacity	52 Ah
Baseline Assumptions	
Scrap Rate	11.7% [17]
Maintenance-/Downtime	15%
Energy Demand	46.7 kWh/kWh [11]
Required Staff	2,685 FTE [11,16]
Investment Cost	See ref. [8,11,15,16,18]
Area Demand	See ref. [11]
Specific Output	See ref. [11]

The battery cell production costs depend heavily on material prices, energy costs and location-specific parameters – they are not the primary research objective in this study. The battery production costs in $/kWh are rather used as a baseline to model the potential improvements through digital technology. The underlying parameters for the cost model are taken from the scientific literature [8,11,15–18] and set a baseline scenario, which is used to evaluate the impact of each of the implemented use cases. The input collected in the expert survey is then processed in the model to quantify the impact on the four primary cost driving KPIs which set the stage for an economic evaluation. To offer a comprehensive perspective on how the use cases can influence various facets of battery production, we categorize improvement potentials into the areas of operations, sustainability, and cost. This categorization facilitates a more in-depth discussion of these three aspects later on.

In the online survey, the participants were asked to move a slide bar between -25% to +100% to assess the KPI improvement relative to the baseline. If the baseline is given as a percentage value, the improvements will not be added as percentage points but relative to the baseline value. Example: a 5% improvement of 10% scrap rate results in a recalibrated rate of 9.5%.

Furthermore, the use cases were evaluated independently, rather than as a combination of multiple use cases, allowing for a focused understanding of the specific effects of each digitalization measure. Therefore, not considered in the impact evaluation are:

- Interdependencies between the investigated use cases
- Interdependencies between cost drivers (e.g., machine utilization vs. scrap rates)
- Impact on area demand, dry rooms, material handling and building
- Cost degressions for material supply

Selected Use Cases in Detail

In this chapter, the seven shortlisted use cases are featured with dashboards that contains the output results from the cost model, including quantified KPI improvement potentials, possible cell cost savings and some plant investment figures for the production plant. In addition to the dashboard and a brief description of the use case, its related enabling technologies and key benefits for cell manufacturers are listed.

In essence, the chapter provides a comprehensive examination of the use cases with both qualitative and quantitative results from the expert survey and the cost modelling exercise.

Figure 6 illustrates the seven selected use cases and their respective timeline in the lifecycle of the cell production plant – from planning to start of production (SoP) to operations.

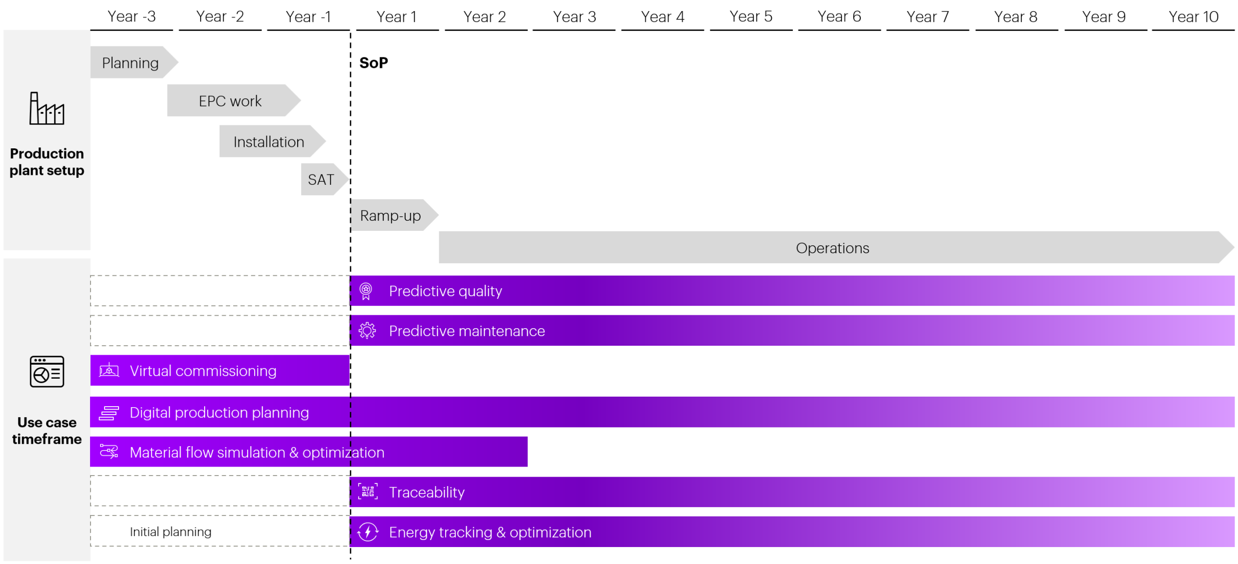


Figure 6: Use case timeframes in reference to a simplified manufacturing plant timeline. EPC = engineering, procurement, and construction. SAT = site acceptance testing. SoP = start of production. A plant setup with only three years from planning to SoP is considered, which can be regarded a fast-track project by an experienced cell manufacturer. For the cost model, the plant operations are assumed to last 10 years.

Virtual commissioning and material flow simulation hold great relevance in the initial phases of the factory planning, helping the cell manufacturer to gain production insights even before the equipment is physically installed in the plant. Digital production planning can also be considered right away from the start, and its impact extends into the later stages of plant operations if the solution is retained.

The simulation tools can be powerful support during the ramp-up phase when production lines are expanded, or additional lines are installed in the Gigafactory. The remaining use cases are deemed to contribute value primarily during the production of cells post-SoP, specifically in the ramp-up and operations phase.

Use Case 1: Predictive Quality

Description

Quality forecasting involves utilizing production data to predict the quality of the intermediate and final product. By analyzing this data, it becomes possible to identify manufacturing and quality issues with the products and take actions. In battery cell production, the final product properties are measured in the end-of-line checks after cells went through an aging process, which can span over multiple days. Intermediate products are usually checked during most the manufacturing process steps, which conceptually sets the foundation for data-driven corrective interventions in the process flow. If the manufacturer was to predict out-of-specification product quality based on historical data early in the upstream processes, e.g. electrode during coating or stacking, the cell or its intermediate parts could automatically be scrapped before they get in contact with electrolyte or they block formation channels and aging racks. This saves resources and allows cost savings through the prevention of additional waste. Quality forecasting can therefore both increase the product quality and reduce the rate of scrap, contributing to more efficient and effective manufacturing processes [19–22].

Impact on production

Predictive quality was found to have a high impact on scrap rates and can therefore lead to a significant production cost reduction by lowering the material waste. By utilizing predictive quality techniques, potential quality issues can be identified, made visible to the operator and addressed in an intelligent and automatic way. Other key benefits arise for the later stages of the product lifecycle when a sophisticated quality management system (QMS) helps to reduce the likelihood of costly warranty returns and therefore the loss of corporate reputation.

Related use case

Quality gates are control and decision points that allow for advanced process control and feedback loops in production process chains. They help cell manufacturers to promptly troubleshoot production issues through the early detection of production failures and quality parameter deviations, though it adds complexity to the manufacturing operations [23]. The establishment of quality gates are especially relevant for materials and parts after the completed electrode coating, calendaring, electrode stacking and cell formation procedures.

UC1: Predictive quality

		Saving potential (low – high)	[%]
Operations	Scrap		6.1
Operations	Downtime		0.1
Operations	Staff		0.0
Sustainability	Energy		5.2
Sustainability	Emissions		5.3
Cost	Material		0.6
Cost	Manufacturing		1.0
Cost	Overall		0.7

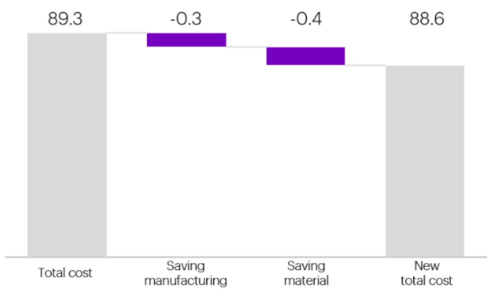
Enabling technologies:

- Scanning / marking technologies
- Manufacturing execution system
- Camera systems
- Process modelling & simulation
- IIoT platform
- Information model / ontologies
- Machine learning
- Soft sensors
- Edge devices
- Cloud computing

Key benefits:

- Improved product quality
- Significant scrap reduction and hence material cost savings
- Improved energy usage
- Reduced warranty cost
- Improved customer satisfaction

Cell production cost impact [$/kWh]



Investment figures

CAPEX: $59–152M

OPEX (p.a.): $3–9M

Saving potential (p.a.): $25.48M

Payback period: 3–12 years

Timeframe: SoP–EoP

Use Case 2: Predictive Maintenance

Description

Sensors have the capability to gauge and log the present condition of equipment on the production line. For example, vibration sensors can detect abnormal vibrations that may indicate potential issues with rotating machinery (e.g., in mixers), while temperature sensors can identify unwanted overheating (e.g., in formation racks). This data is essential for performing time-series analysis, which is a foundation of predictive maintenance. The historical and current data help in identifying patterns, trends, and anomalies that can be used to predict when maintenance is required. By continuously monitoring the equipment, sensors can quickly detect any deviations from normal operating conditions. This allows for the early identification of potential faults or malfunctions, helping maintenance teams to intervene before a critical failure occurs. Optimal timing for inventory planning and replacing spare parts can be achieved, ultimately preventing unexpected equipment failures during production, ensuring smoother operations and minimizing downtime [24–29].

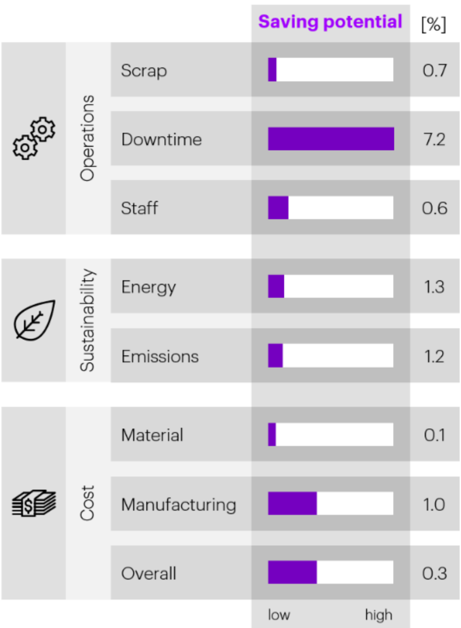
Impact on production

The analysis suggests that predictive maintenance has a high potential to reduce the downtime in lithium-ion battery cell production lines and plants, thus improving the overall OEE. It reduces maintenance-related issues and minimizes downtime throughout the battery production by predicting machine failures before they can lead to a decline in product quality or result in machine downtime. However, when it comes to sustainability metrics, scrap rate, and required staff, the impact of this use case is low.

Related use case

Machine monitoring involves the continuous monitoring and analysis of machine performance and operating conditions. By collecting and analyzing data from machines and sensors, machine monitoring enables the detection of anomalies, deviations, or signs of potential failures in the production equipment. Through machine monitoring, manufacturers can gain valuable insights into the complex relationship between process parameters and the condition of asset health. This data-driven approach helps optimize maintenance schedules, improve overall equipment efficiency, and lower the maintenance costs.

UC2: Predictive maintenance



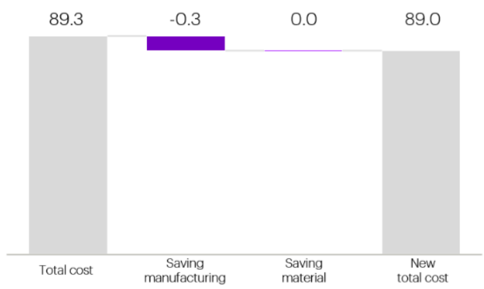
Enabling technologies:

- IIoT platform
- Smart/soft sensors
- Manufacturing execution system
- Machine learning
- Edge devices
- Cloud computing

Key benefits:

- Downtime reduction and hence lower manufacturing cost
- Increased OEE and equipment lifetime
- Maximized equipment utilization
- Improved spare parts inventory planning
- Enhanced safety

Cell production cost impact [$/kWh]



Investment figures

CAPEX: $29-77M

OPEX (p.a.): $2-7M

Saving potential (p.a.): $11.72M

Payback period: 4-22 years

Timeframe: SoP–EoP

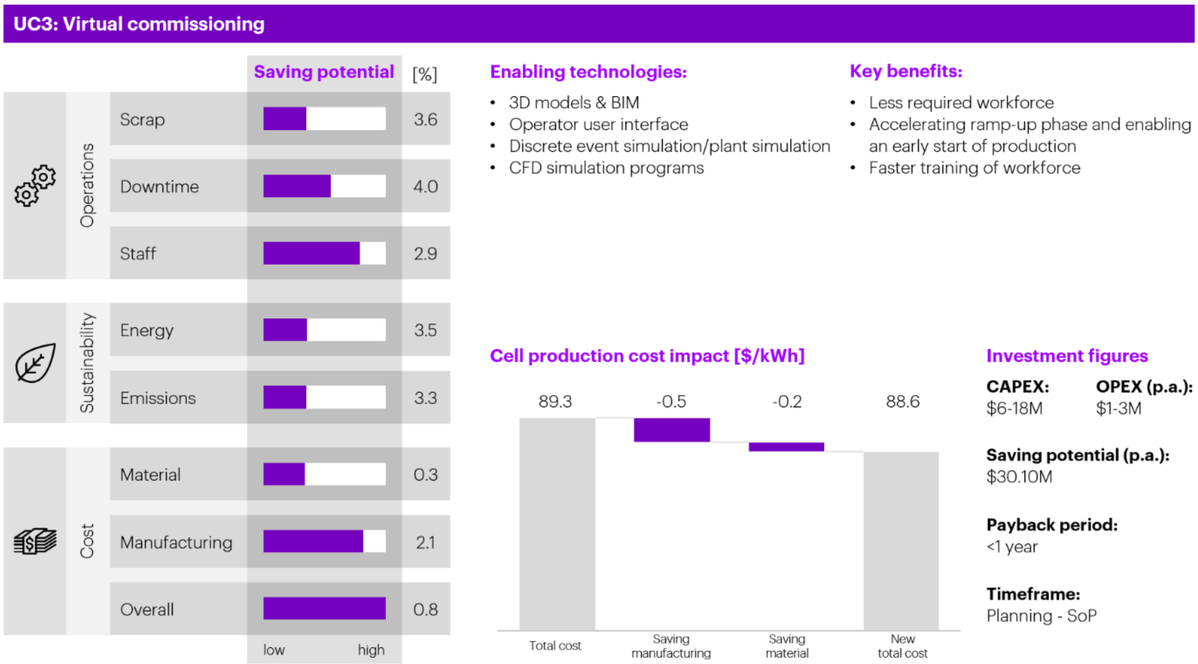
Use Case 3: Virtual Commissioning

Description

Virtual commissioning is a process that uses simulations to test and validate the functionality of a machine or production system before it is physically installed. It involves creating a virtual model and running simulations to analyze the machine's performance, identify potential issues, and optimize its operation. This allows for early detection and resolution of machine implementation problems, reducing the time and cost that are associated with traditional commissioning processes. The insights gained during this virtual testing phase can then be applied to the real-world production ramp-up, which helps to foresee implementation issues and allows to begin with the worker training earlier. By connecting the created model with MES, CAD models, or BIM system, functional tests and collision detection can be automated and conducted early. Generally, virtual commissioning facilitates a smoother and faster ramp-up, once the machines are in place [30].

Impact on production

Virtual commissioning has its highest potential impact on operations such as the required staff. By simulating the production line early on, cell manufacturers can identify opportunities to streamline and automate their processes and hence reduce the need for manual labor. In addition, the ramp-up can be done faster using simulations in training. On the long run, downtime and scrap rate can also benefit from virtual commissioning via the early-stage identification of production issues that could lead to unwanted downtime. This leads to an overall large impact on the manufacturing costs. Considering the sustainability aspects in cell production, energy and emissions can be lowered through virtual commissioning because manufacturers can identify energy-intensive steps and areas and streamline them for improved energy efficiency.



Use Case 4: Digital Production Planning

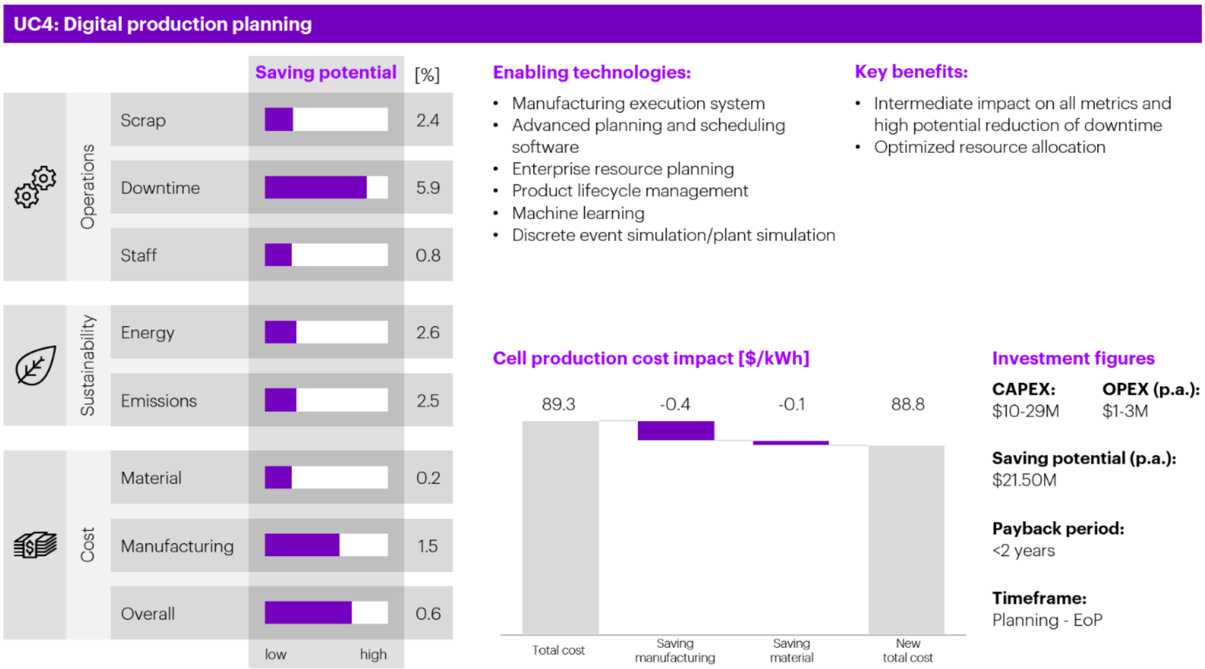
Description

Digital production planning leverages a variety of digital tools such as Advanced Planning and Scheduling (APS) systems and simulations of plant operations. They contribute to a more precise and efficient planning approach, thereby enhancing the overall production workflow. By integrating digitalization, this method streamlines plant operations, increases accuracy, and ultimately leads to improved manufacturing outcomes [3]. Commencing digital production planning early in parallel with product development or utilizing it to optimize resources, processes, and materials during ongoing production is already feasible. Integrating digital production planning with systems like PLM, MES, and ERP yields optimal outcomes. This approach advances cross-functional collaboration among various manufacturing departments, promoting seamless information collection and sharing across multiple departments.

In a practical application, development engineers use CAD software for cell and component design and manufacturing engineers plan production processes digitally, simulating and creating a digital model of the plant to optimize space and reduce bottlenecks.

Impact on production

The implementation of digital production planning offers benefits especially in the operational category 'downtime'. By leveraging advanced digital tools like APS systems and simulations, manufacturers can optimize the production process, leading to more efficient maintenance practices and higher machine uptime. Digital production planning can enhance the manufacturability of a new product. At the same time, it allows for better resource allocation and hence comes with small positive impact on the staff requirements. Additionally, manufacturers can identify areas of improvement in the production process and implement strategies to minimize waste and defects and hence reduce the scrap rate. This leads to cost savings, improved product quality, and increased efficiency in the production line.



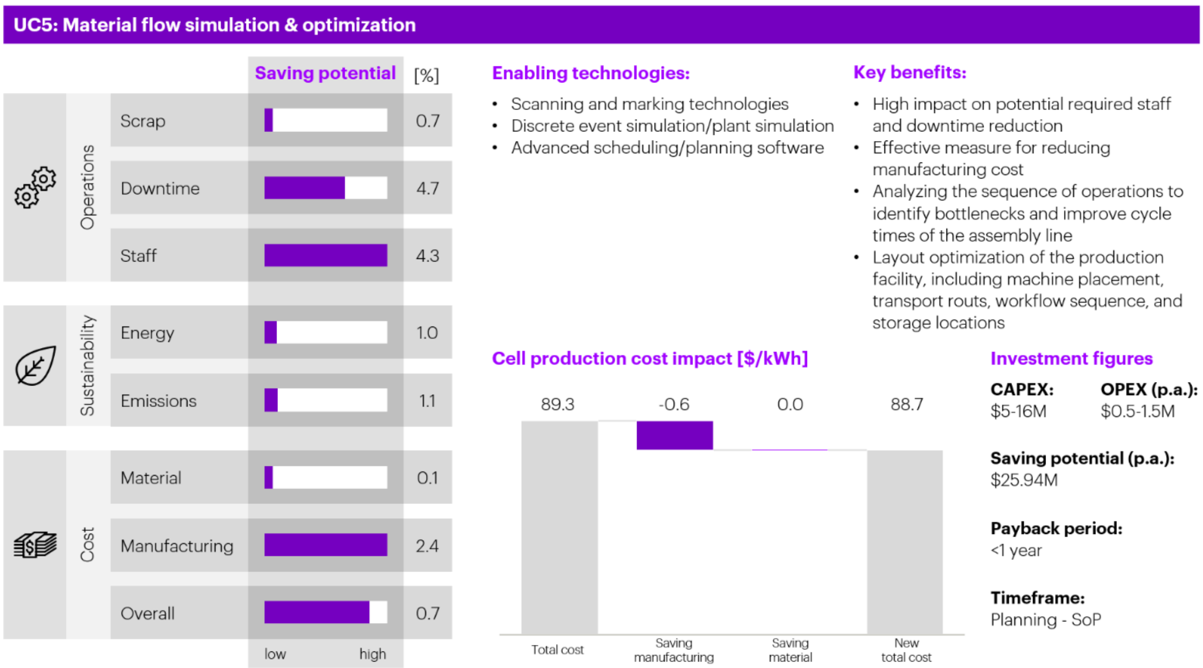
Use Case 5: Material Flow Simulation & Optimization

Description

Material flow simulation and optimization involve the strategic use of simulation tools, providing significant benefits to cell manufacturers, particularly in the pre-planning and initial phases of establishing a new production plant. This methodology centers on the customization and refinement of the factory blueprint's production elements. It can involve creating a realistic 2D or 3D model of the production plant that includes modeling processes, mapping machines, materials, and people to visualize and analyze the overall production flow, indicating potential bottlenecks and areas for process improvement. The utilization of these tools empowers manufacturers to proactively address potential obstacles, optimize material flow dynamics, and elevate the overall efficiency of the battery cell manufacturing process. Consequently, this approach leads to a more efficient and effective production setup for battery cell manufacturing [31].

Impact on production

The implementation of material flow simulation and optimization in battery cell production has shown a high potential impact on overall maintenance and downtime as well as required staff. By employing material flow simulation tools during the planning phase, manufacturers can rearrange and streamline the production elements and optimize the material flow, ensuring a smooth and efficient production setup. As a result, productivity can be increased due to the identification of bottlenecks such as local buffers and disruptions in the manufacturing process. Also, the staff requirements are reduced, e.g., due to optimized (robotic) intralogistics solutions and a streamlined layout of the factory. All the potentials in the operations have a strong effect on the manufacturing costs. Furthermore, material flow simulation and optimization reduces scrap rates in electrode production by identifying inefficiencies or inhomogeneities in the material flow. In terms of energy consumption and emissions, this analysis indicates that there is minor potential to reduce both to improve sustainability.



Use Case 6: Traceability

Description

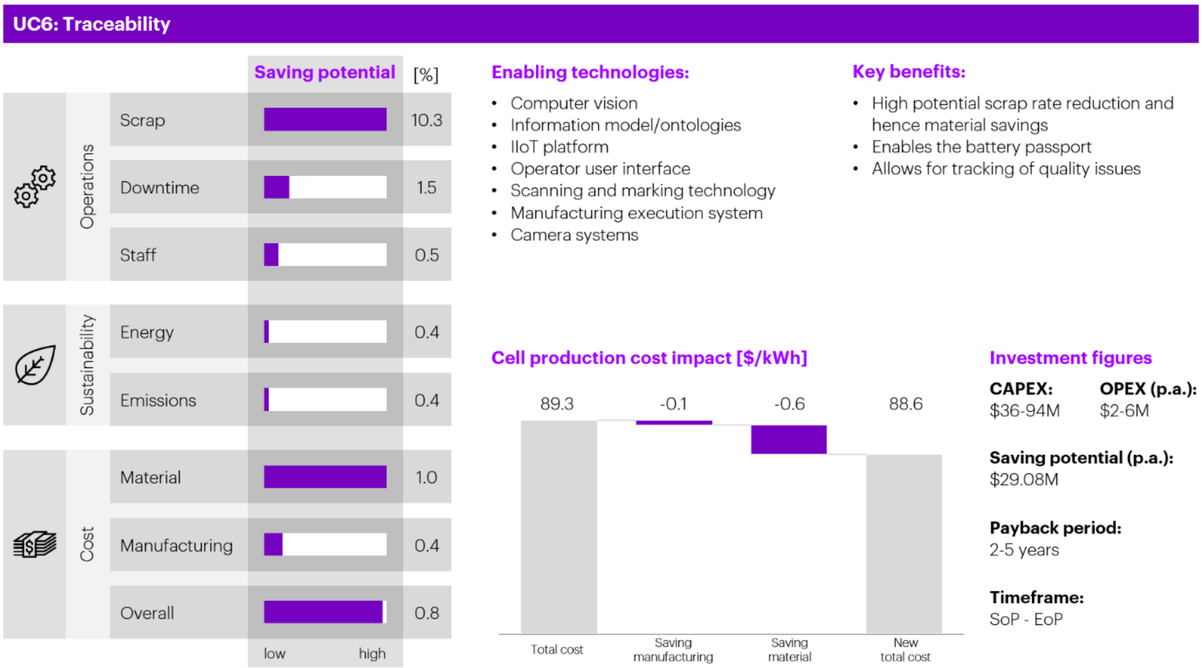
Traceability in battery cell production allows the tracking of all battery materials and components, intermediate parts, and finished products to obtain a complete product structure with traced parts. It is also used to record production parameters throughout the manufacturing process and map them to the respective parts and products. This includes data on machine operations, quality metrics, and process variables that are relevant for the production of individual cells. These recorded parameters can be seamlessly traced back to a specific batch, electrode sheet, or cell that they are associated with. A comprehensive traceability system enhances accountability, quality control, and the ability to address any potential deviations or issues in the production process. This approach generally enhances product quality and simultaneously reduces waste, which contributes to more efficient and effective manufacturing processes [3,14,32,33].

Impact on production

Traceability has particularly large impact on scrap rates and, consequently, material costs in the battery cell manufacturing process. By implementing a comprehensive traceability system, it becomes possible to track raw materials, semi-finished products, and the finished battery cell throughout the production process. This enables the identification of any deviations or issues that may arise, allowing for timely intervention and corrective actions. Furthermore, product and production data can and should be stored by the cell manufacturer for several years in case that any quality claims arise when the customer is using the product.

Enabled service

The battery passport is a digital documentation system central to sharing comprehensive data on batteries, including chemical material composition and operational lifecycle details. It is part of the EU regulatory framework and is going to become mandatory for large parts of the battery industry by 2027. Traceability in production and in the value chain beyond is essential to ensure a beneficial level of transparency, validate information, and support circular economy initiatives, providing stakeholders with the necessary information for informed decision-making, ethical practices, and sustainable battery management. It aligns with industry and policy goals, enhancing value and benefits across the battery value chain [34,35].



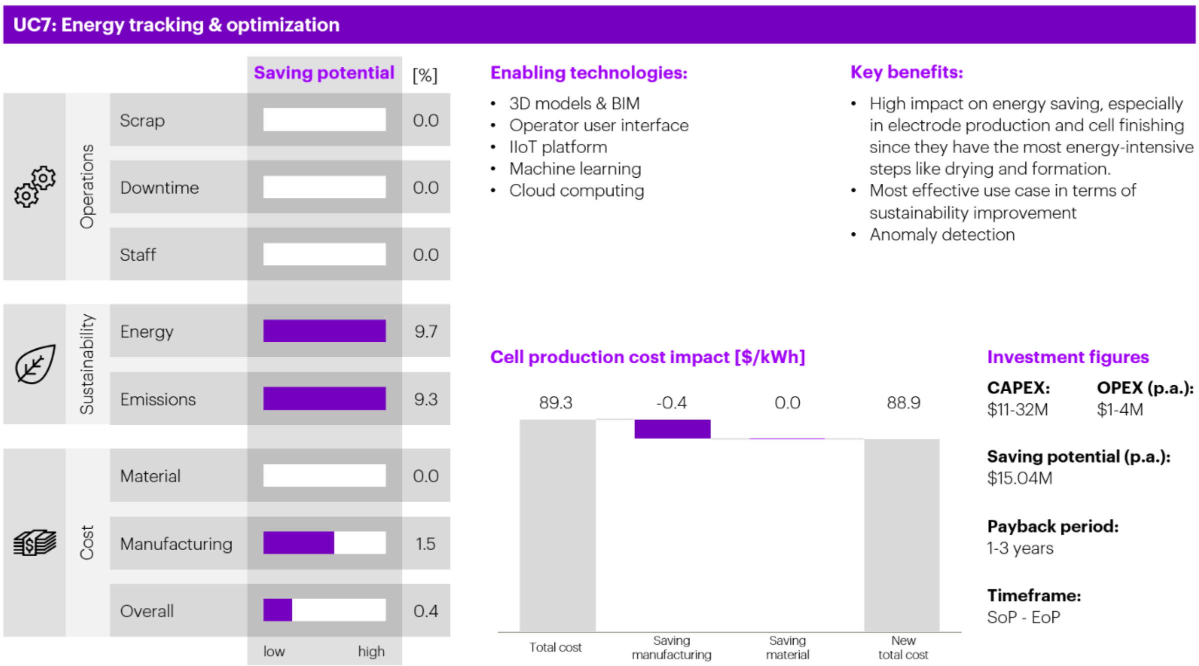
Use Case 7: Energy Tracking & Optimization

Description

End-to-end tracking of energy consumption and ecological impacts is the basis for general environmental and sustainability practices in cell manufacturing. Based on the production data, strategies such as harnessing waste heat generated during air processing in dry rooms can be implemented. Additionally, the implementation of prescriptive management of certain process conditions, e.g., temperature distribution in the formation and aging areas, contributes to maintaining consistent production standards. The implementation uses various previously mentioned technologies such as 3D Models, BIM and the IIoT platform. In addition, software energy management solutions using ML can aid the proactive energy management or identify anomalies. Moreover, the tracking of power consumption across all production assets enables a thorough understanding of their energy usage. Integrating an intelligent energy management system (EMS), battery production can ultimately achieve higher energy efficiency, reduce waste, and minimize environmental impact, aligning with sustainable manufacturing best practices [36].

Impact on production

Energy tracking and optimization logically promises a high positive impact on energy usage and emissions, contributing to sustainability efforts in manufacturing and at the same time leading to reduced manufacturing costs. According to the results of the expert survey, it has no direct impact on other metrics such as operations or material costs.



Result Overview

This chapter contains the side-by-side comparison of all seven uses cases and a discussion based on the results of the survey and cost modelling exercise. Figure 7 summarizes the findings for the quantified production aspect improvements in form of a heatmap.

		UC 1 Predictive quality	UC 2 Predictive maintenance	UC 3 Virtual commissioning	UC 4 Digital production planning	UC 5 Material flow simulation & optimization	UC 6 Traceability	UC 7 Energy tracking & optimization
Operations	Scrap Rate	6.1%	0.7%	3.6%	2.4%	0.7%	10.3%	0.0%
	Downtime	0.1%	7.2%	4.0%	5.9%	4.7%	1.5%	0.0%
	Staff	0.0%	0.6%	2.9%	0.8%	4.3%	0.5%	0.0%
Sustainability	Energy	5.2%	1.3%	3.5%	2.6%	1.0%	0.4%	9.7%
	Emissions	5.3%	1.2%	3.3%	2.5%	1.1%	0.4%	9.3%
Cost	Material	0.6%	0.1%	0.3%	0.2%	0.1%	1.0%	0.0%
	Manufacturing	1.0%	1.0%	2.1%	1.5%	2.4%	0.4%	1.5%
	Overall	0.7%	0.3%	0.8%	0.6%	0.7%	0.8%	0.4%
	Cell cost [$/kWh]	88.71	89.06	88.60	88.82	88.70	88.62	88.97

Figure 7: Direct use case impact comparison based on cost model calculations with survey results as input. Data as already shown in the use case dashboards of the previous section. The implementation of the use cases leads to a relative cost reduction compared to the baseline scenario at 89.35 $/kWh, which is expressed as the new cell cost.

The participants' estimations were expressed as percentage values relative to a baseline scenario without the implementation of the respective use case. Note that input was collected on a manufacturing step level (mixing, coating, ...) and used for cost calculations in the model. The full data sets in Appendix Figure 11 and Figure 12 show the results over all manufacturing steps processed into single values per KPI and use case. To begin, we summarize the findings with a description of the impact on the cost drivers:

Scrap rate

The results as shown in Figure 7 show that the implementations of traceability and predictive quality and stand out as particularly promising measures for reducing the scrap rate by 10.3% and 6.1%, respectively. These specific use cases could therefore significantly mitigate waste in the manufacturing process, maximize material use efficiency and enhance the yield of products within specifications. Interestingly, the third biggest impact among the investigated use cases was found for virtual commissioning with 3.6% improvement potential. This is likely because simulating and optimizing production processes before their physical implementation, leads to fewer manufacturing errors and less waste. According to 'the rule of ten', the early-stage identification of errors typically results in cost savings compared to correcting them at a later stage. Minor scrap rate improvements (<2.5%) can be achieved with material flow simulation, digital production planning and predictive maintenance.

As the complete data set in the Appendix shows, this effect comes through an improved electrode production process, rather than an impact on the cell assembly and finalization steps. Cell scrap is a multicausal problem. Digital technologies help to gather information and reveal some of the causes. Subsequently, an engineer or perhaps even a smart algorithm can take actions to prevent this. The cost model calculations in this study indicate relative KPI improvements compared to a baseline scrap rate of 11.7% but use cases might have an even bigger lever that can help manufacturers reach ambitious targets of <2% cell production scrap. Since this is one of the biggest levers for a reduction of battery production costs, the number of finished cells that unfortunately have to be scrapped or cannot be sold must honestly be monitored and analyzed by the cell manufacturer in a real production environment.

Maintenance and downtime

In terms of minimizing downtime, the most substantial impact comes from adopting predictive maintenance technologies, allowing for a 7.2% reduction. Digital production planning (5.9%) and material flow simulation & optimization (4.7%) closely follow on rank two and three. This suggests that the integration of predictive maintenance is pivotal for averting unexpected machinery failures and optimizing production efficiency.

The implementation of predictive maintenance plays a crucial role in minimizing downtime and optimizing production efficiency especially in electrode production and finalization processes. By adopting this technology, the manufacturing facility can find and address potential machinery failures before they occur, reducing unplanned downtime. This proactive approach enhances the reliability of production processes, ensuring continuous operation and minimizing disruptions. Additionally, digital production planning and material flow simulation/optimization contribute to overall efficiency, emphasizing the importance of holistic strategies in improving the reliability and performance of battery cell manufacturing.

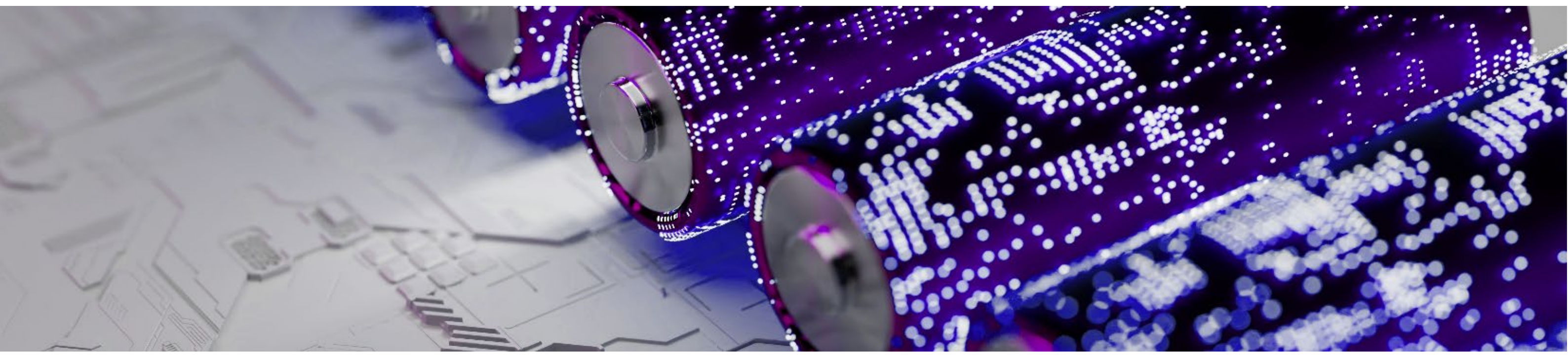
Overall, the increased productive time of the shopfloor assets can boost the availability factor of the plant OEE by a couple of percentage points, if the plant is already running in a fairly streamlined setup.

Required staff

While the overall changes in staff brought about by the introduction of use cases are deemed ‘slight’ with a maximum change of 4.3% for material flow simulation and optimization, the consequential reduction in a plant with 2,685 employees could amount to 116 Full-Time Equivalents (FTE). Notably, the implementation of software-based use cases (UC3-UC5) has the potential to further diminish the required workforce and therefore reduce the labor share in the battery production cost, especially in Western countries. Note that this study does not take into account a potentially increased demand for software engineers or other staff to configure, implement, maintain and troubleshoot the desired IT solutions.

Energy consumption and emissions

The modelling of the sustainability metrics reveals that energy tracking and optimization yield the most significant impact on reducing energy usage and emissions by 9.7% and 9.3%, respectively. Predictive quality follows closely with 5.3% KPI improvement. The calculations confirm that smart energy management solutions can substantially contribute to more sustainable battery production and plant operations, which directly translates into a more cost-efficient production.



Cost

The improved operations and sustainability parameters enabled by the use cases lead to material, manufacturing, and overall production cost savings, as shown in the lower part of Figure 7. The material costs could be reduced by 0.6-1.0% through predictive quality and traceability, respectively. This effect is mainly driven by a lower scrap rate that could be achieved with measures that enhance the product quality. The manufacturing cost levers are higher and virtual commissioning and material flow simulations stand out with reduction potentials of 2.1% and 2.4%, respectively.

Translated into overall cost savings for the modelled battery cell production plant, the seven investigated use cases land in a range of 0.3-0.8%. Virtual commissioning, traceability, material flow simulation, and predictive quality appear as the most potent, offering an approximate 0.7-0.8% reduction potential. Predictive maintenance, digital production planning, and energy tracking and optimization trail closely behind with cost reductions of 0.3%, 0.6%, and 0.4%, respectively. Predictive maintenance is positioned as having the least impact on cost reduction.

This underscores the notion that specific use cases, particularly those related to virtual planning and manufacturing process optimization, have the greatest potential for achieving cost savings in industrial contexts.

Figure 8 shows the financial figures, including the cell production costs savings and the investment requirements for the use cases when applied to a 40 GWh/a production plant.

		UC 1 Predictive quality	**UC 2** Predictive maintenance	**UC 3** Virtual commissioning	**UC 4** Digital production planning	**UC 5** Material flow simulation & optimization	**UC 6** Traceability	**UC 7** Energy tracking & optimization
Invest	CAPEX	$59-152M	$29-77M	$6-18M	$10-29M	$5-16M	$36-94M	$11-32M
	OPEX	$3-9M	$2-7M	$1-3M	$1-3M	$0.5-1.5M	$2-6M	$1-4M
	Annual savings	$25.5M	$11.7M	$30.1M	$21.5M	$25.9M	$29.1M	$15.0M
	Payback period	3-12 years	4-22 years	<1 year	<2 years	<1 year	2-5 year	1-3 years

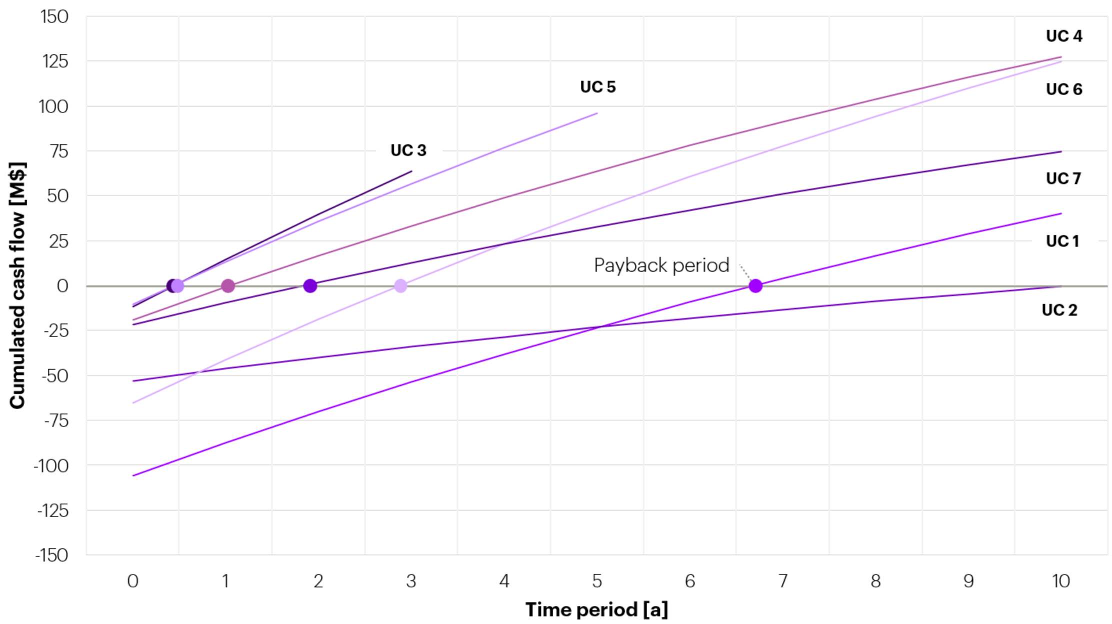


Figure 8: Financial numbers for the seven use cases. Investment CAPEX and OPEX are combined with the positive cash flow from the annual saving potential related to lowered cell production cost, this leads to the break-even/payback period. The cumulated cash flows for a period of 10 years are illustrated for each use case in the base-scenario. For virtual commissioning and material flow simulation, shorter timeframes for a saving duration of 3 and 5 years are assumed.

The economic impact of the top four use cases can lead to annual savings of approximately $25-30M each, based on the calculated production cost reduction per cell. This is used as a positive cashflow figure that stands against the investment requirements and operational expenditures for the use cases and related enabling technologies.

The assumptions for the capital (CAPEX) and operational expenditures (OPEX) are based on Fraunhofer FFB and Accenture industry benchmarks and upscaled suggested pricing offers from solution vendors. The optimistic, baseline and pessimistic scaling factors for hardware and software are shown in Appendix Figure 13.

When comparing the initial capital investments for the use cases, software-based solutions such as material flow simulations, virtual commissioning, digital production planning and energy tracking stand out at the most affordable options in a range of $5M to $32M for a Gigafactory. The other use cases that additionally require OT investment such as sensors and robots or more sophisticated software platforms (e.g., MES, ERP) are significantly more expensive and the possible price span is larger. Based on pessimistic price scaling assumptions, predictive quality stands out as the single most expensive use case with $152M initial investment due to the large list of required enabling technologies. All scaled-up operational expenditures for the use cases remain within the range of a single-digit million amount.

The payback periods are calculated for the pessimistic and optimistic scenario and given as range of years after start of production, in which the use case will likely reach the break-even point. All seven use cases can reach this point within the ten years of plant operations, turning cash-flow-positive in the base and optimistic scenario. Certain use cases might yield quicker returns on investment taking the variability in the complexity and impact of different measures into account. The fastest amortizing solutions are the software-heavy use cases virtual commissioning (<1 year) material flow simulation (<1 year), digital production planning (<2 years) and energy tracking (<3 year). Traceability is heavy on initial investments, but the annual cost saving potential may result in amortization in 2-5 years. Predictive quality and maintenance might reach the breakeven point after 3-4 years in the optimistic expenditure-scaling scenario, but in the pessimistic case this could be pushed beyond the plant runtime. It is important to emphasize the need for special attention when investing in hardware-heavy use cases. Hardware costs can escalate rapidly, and the potential for smaller cost degression effects should be carefully considered. Managing and optimizing hardware spendings are essential to prevent these costs from rising. Software-based solutions generally offer more scalability compared to hardware-intensive approaches.

The results as shown in Figure 8 suggest that, from an economic perspective, all seven uses should be implemented because they result in a positive net present value. However, the calculated break-even points for the cash flow should be approached with caution and viewed as indicative, because solution providers use various pricing strategies for different customers and battery manufacturing plants. Two examples: newly developed solutions are offered at a lower price and improved as part of the customer project in form of a co-development, while off-the-shelf solutions that are already feature-complete are sold at higher prices. Certain enabling technologies or use cases are billed as Software-as-a-Service (SaaS) on a $/kWh-premium basis, deviating from traditional one-time investments or annual fees. Pricing strategies like this contribute to a broadened range of cost parameters, introducing a level of complexity and potentially obscuring the clarity of the results of the fiscal analysis.

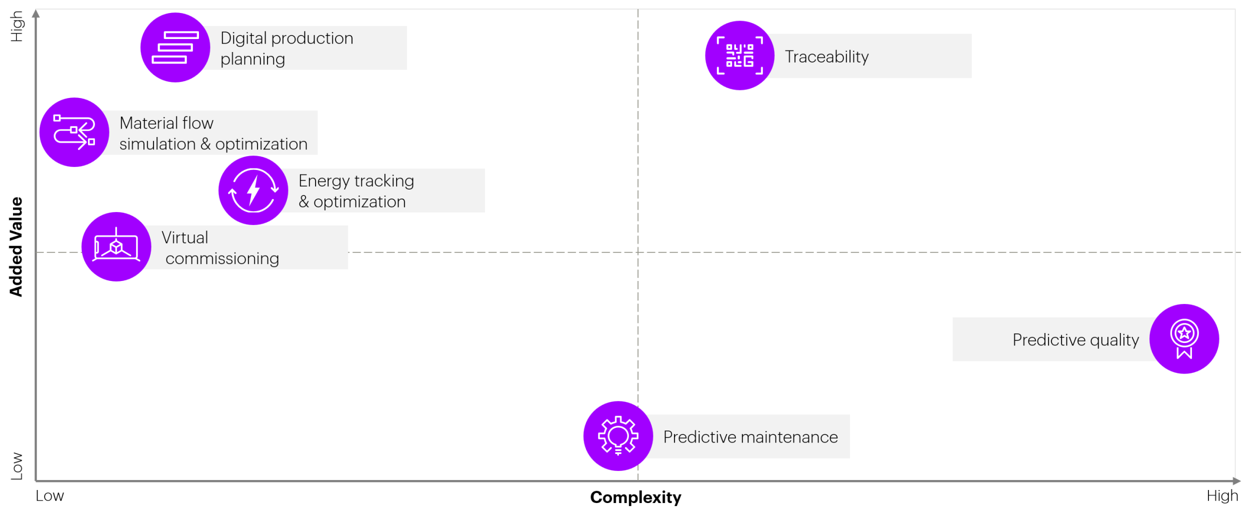


Figure 9: Added value and complexity comparison. The positioning of the use cases in this comparison is qualitatively based on the previously discussed results and considers the investment figures. The best use cases can be found in the low complexity and high added value quadrant.

If the use cases are placed in a benefit-effort-matrix (Figure 9) that sets their complexity in relation to their added value, a further basis for decision-making is obtained.

The use cases virtual commissioning, digital production planning and material flow simulation are the low-hanging fruits that are rather easy to implement and result in a high added value, mainly because of their scalable software-based nature. Their biggest impact can be achieved when employing them already in the factory planning phase for quick iterative improvements, but their benefits will reach into the late-stage operations as well. Energy tracking and optimization will pay off in the later stages of the plant lifecycle when the production has been ramped-up, but the shopfloor should be designed to have all necessary sensors and controls for complete energy and utility monitoring. While the implementation of end-to-end traceability is somewhat complex, is a must-have use case when considering aspects of regulatory compliance, customer expectations and digital supply chain management. In the European Union, batteries will require a carbon footprint declaration and receive an obligatory label – the cell manufacturer must be able to provide this information and hence requires data sovereignty. Hence, an energy management system is an important building block of the IT/OT solution architecture that can help to provide and process that data. Compared to the other top use cases, predictive maintenance offers less added value because its direct impact is limited to the machine downtimes but not big cost levers like a production scrap reduction.

Nevertheless, it is a powerful tool that should show up on every cell manufacturer's production technology roadmap. Predictive quality could be implemented at a later stage, as it is associated with a high upfront investment. It also requires the most practical experience in cell manufacturing and actual product and manufacturing data, which makes it challenging to launch a software system upfront, which can make accurate quality predictions. However, the overall plant IT/OT architecture should be designed in a way that it is ready for future quality management system upgrades and additional solutions. The remaining use cases that are listed in Table 3 that did not qualify for the in-depth cost calculations in this study can also be considered as relevant for a cell manufacturer if the company seeks to modernize and optimize the production processes or plant operations. Furthermore, there are plenty of commercial digital solutions that support the day-to-day workflow of a company but are not directly related to the specifics of battery cell production. Some examples are applications or software suites for enterprise, project, document or risk management. While these aspects are beyond the scope of this study, it is important to highlight that they should be integrated into the overall solution architecture as well.

Conclusion

We summarize the comprehensive use case analysis presented in this study with this set of strategic recommendations to enhance battery production:

- Always check for economic viability: carefully assess the financial implications of digital solutions, prioritizing those with the most significant impact on cost reduction and operational efficiency.
- Prioritize solutions for a high-quality electrode production: focus digitalization efforts on electrode production processes to leverage the highest potential for cost savings and efficiency gains.
- Focus on software-based solutions: scalable, software-based digital applications typically require less investment and easier to implement than OT-heavy manufacturing solutions.
- Enhance energy efficiency: invest in energy management solutions to gain more control about sustainability metrics and set more ambitious efficiency targets that will drive down both energy consumption and production cost.
- Upgrade for predictive technologies: especially established players with already fairly optimized plants should implement traceability, predictive quality and maintenance solutions to further enhance operational reliability and reduce waste.

Outlook

From roadmaps to working solutions – the implementation of novel smart manufacturing solutions, comes with a couple of practical challenges.

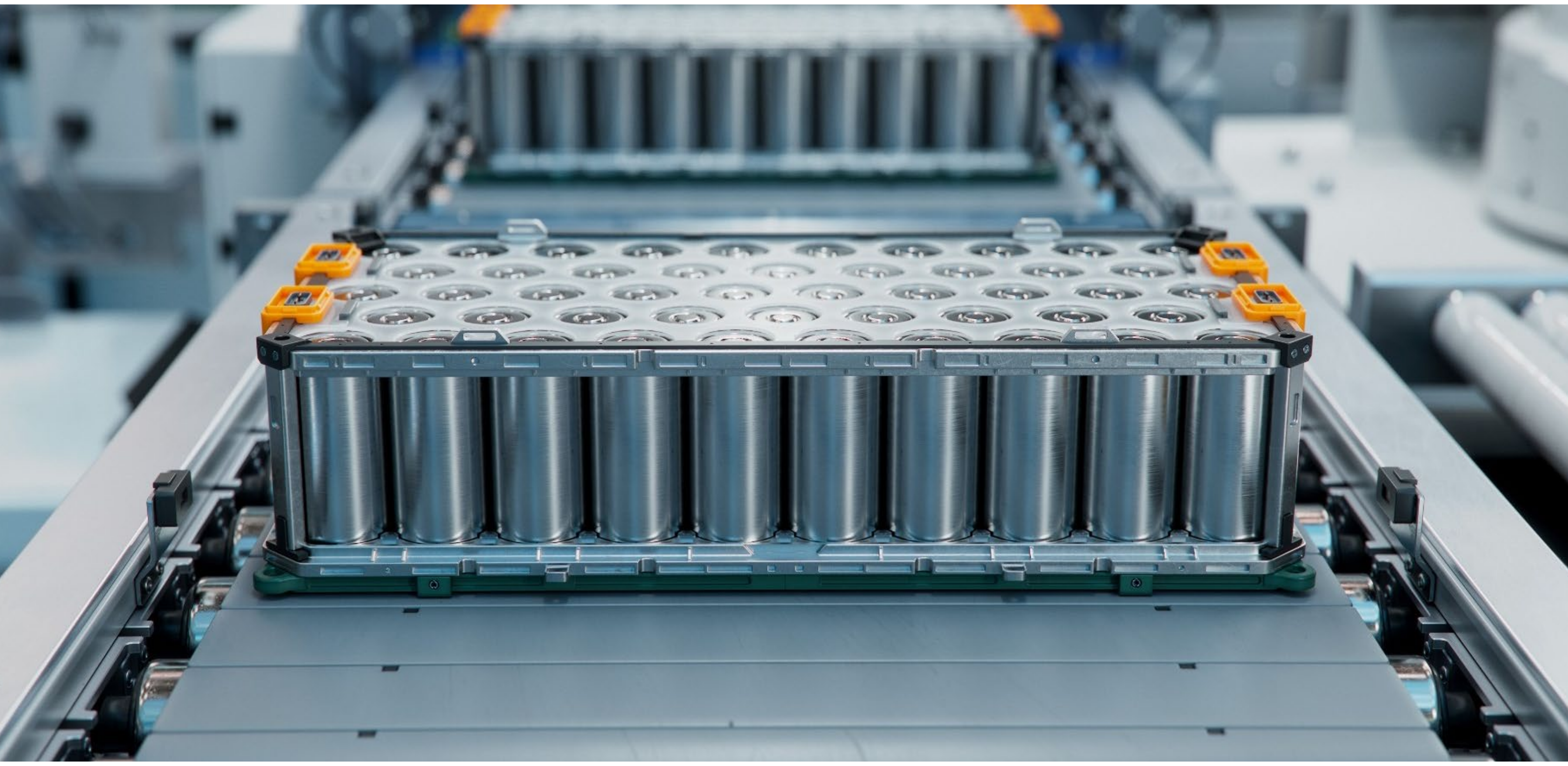
Any additional building block in an IT/OT architecture will add cost and complexity, which must be managed by the manufacturer to realize the technological benefits. The efforts to design, configure and roll-out a new enabling technology and use case should not be underestimated, because this can easily cause budget overruns or project delays. Therefore, for a successful IT implementation, a resilient plan with realistic roll-out timelines and proper internal and external resource allocation is required. Plus, the solutions must be planned and built to be scalable, interoperable, and somewhat future proof, e.g., if the cell technology and related product parameters change or the manufacturer plans another plant in a new market.

Data is at the core of this digital revolution. Its significance cannot be overstated, with the quality, availability, quantity, structure, flow, ownership, and security of data all being relevant aspects. Challenges such as data access limitations for machine manufacturers impede the development of digital services, underscoring the need for openness to digital innovation, adherence to industry standards (e.g., OPC UA), and a culture of cross-company collaboration. Moreover, appreciating the value of data as an asset is critical for unlocking new business models for battery cell manufacturers.

The risk of failing to adopt the right digital technologies at the relevant phases of the plant lifecycle can lead to missed opportunities and financial underperformance. On the other hand, overemphasizing technologies that do not yield a return on investment for the manufacturer constitutes a misuse of resources. Both extremes highlight the importance of making informed timely investment decisions to maintain a competitive edge, considering factors such as cost savings, location advantages, and using the strategic benefits of being a late mover.

In battery production, achieving an efficient production is crucial to stay financially viable and maintaining a market leader position at the same time. Conversely, the absence of digital solutions can lead to efficiency losses, competitive disadvantages, and higher production costs, thereby stressing the differentiation potential of digitalization in enhancing sustainability and market position.

There is a risk that manufacturers fail to identify the right digital technologies, invest in them at the relevant point in the plant lifecycle, and actually benefit from short payback periods. This emphasizes the struggle of becoming or staying competitive in the battery industry, which necessitates technically well-thought-out yet timely investment decisions. Lastly, to put it in the broader perspective of world-class cell manufacturing, there are several other competitive factors that will decide over the success of a battery manufacturing project. These include location factors such as subsidies, energy prices, availability and affordability of skilled workforce, access to sufficient production capacity and raw materials at the best purchasing conditions, and of course not to forget: a top product.



Summary and Key Findings

In this Whitepaper, we present digital technologies in battery cell manufacturing and an evaluation based on an industry expert survey and a cost modelling exercise.

Beyond the physical realm of the shopfloor, the digital space comprises three layers: enabling technologies, digital twins and use cases. Enabling technologies refer to foundational tools and systems that, when integrated with digital models of the factory, equipment, or product, facilitate the implementation of value-adding use cases. This study includes a catalog of digital technologies, from which a shortlist of high-potential use case options is derived. The selected seven use cases are predictive quality, predictive maintenance, virtual commissioning, digital production planning, material flow simulation & optimization, traceability, and energy tracking and optimization.

In the baseline scenario of a 40 GWh/a lithium-ion battery cell production plant, the cost breakdown includes 71.4% for materials, 10.3% for machines, 6.9% for labor, and 4.6% for energy costs. Our analysis of the impact of digitalization involves quantifying the effects of the individual use cases on the four primary cost drivers, which are denoted by the production parameters: scrap rate, maintenance and downtime, required staff, and energy consumption. The results of the industry expert study suggest that a scrap rate reduction is the most desirable outcome when dealing with digital solutions.

The cost modelling results show that the implementation of use cases can lower the battery production cost by up to 0.8% per use case, which translates into an annual saving potential of $30M per year in the default production scenario. Material cost can be reduced by 1.0% through the implementation of predictive quality or traceability solutions, while manufacturing cost benefit from virtual commissioning or material flow simulations with potential reductions of up to 2.4%. Besides their positive impact on the cell production costs, the featured use cases promise a boost to the plant's overall equipment effectiveness by enhancing the battery cell product quality and increasing the machine uptimes, while allowing a more efficient production through reducing the demand for energy and manual labor. Energy tracking and optimization is found to have the potential for a 9.5% reduction in energy consumption. Especially the initial stage of battery cell manufacturing, the electrode production, emerges as the primary beneficiary of digitalization efforts, with significant potential for improvements in scrap reduction, energy optimization, and maintenance efficiencies. This area is singled out for its significant impact on both overall production costs and environmental footprint.

The cash flow analysis suggests that an investment into each of the seven use cases leads to a payback period with a breakeven point after a few years of plant operation. With payback periods of only 2 years, software and simulation-based solutions are a less risky investment and hence more attractive to be implemented in a battery cell production plant as 'must-have' solutions. Only in a pessimistic cost-scaling scenario for hardware-heavy solutions, predictive quality and maintenance, the cost savings do not outweigh the high upfront investments in the plant runtime. A thorough examination of these solutions is necessary, incorporating price quotations tailored to the actual plant size. On the long run, however, the pricier investments should have a greater impact because they offer a larger production cost saving potential. This does not apply to predictive maintenance, for example, as the benefits have not proved to be all that impactful. This again underlines the need to carefully weigh up the costs and benefits when deciding to invest in digitalization, especially when the use case appears as 'nice-to-have' or futuristic idea. Acknowledging the assessment of only seven out of 39 potential use cases, the study recognizes the need for further exploration of the remaining digital enabling technologies and use cases.

Considering both economic and technical implications, the low-hanging fruits among the use cases are digital production planning, virtual commissioning, and material flow simulation. They are especially relevant in the early stages of the plant lifecycle, for the planning of new greenfield Gigafactories or brownfield expansions. Traceability is considered a must-have solution because it helps cell manufacturers with future regulatory compliance and quality disputes with the customers. Energy management solutions are also highly recommended and should be found in every new production plant, especially if the cell manufacturer wants to produce batteries with renewable energy only. Next to these essential use cases, the following two represent another layer of added value: predictive maintenance has the potential to decrease machine downtime by 7.2%. It unlocks some added value in factories that already achieve a high level of production line utilization and comes at moderate implementation complexity because it requires a wide set of enabling technologies.

While implementing predictive quality is challenging, a cell manufacturer showcasing its successful application on specific parts or process steps can fine-tune the plant's yield by effectively reducing scrap rates. Finally, thinking the other way around: if cell manufacturers do not use modern digital manufacturing solutions, they might encounter efficiency losses in the mass-scale production, overlook issues related to the product quality, and ultimately forfeit competitive advantages.

In conclusion, digital technologies can be used to produce battery cells more cost effectively at higher resource efficiency. The findings not only underscore the importance of consensus on battery production KPIs and plant performance metrics but also provide a techno-economic approach to assess the intricate dynamics of investments into digital manufacturing solutions. The implications for industry and research are far-reaching, urging stakeholders to consider the strategic prioritization of use cases based on the calculated business impact. As the global battery cell manufacturing industry is growing to reach the terawatt-hour scale in this decade, even the smallest improvement of resource efficiency and sustainability will make an impact. The insights presented in this study clearly demonstrate that this is possible with the help of digitalization.

Appendix

Detailed Survey Results

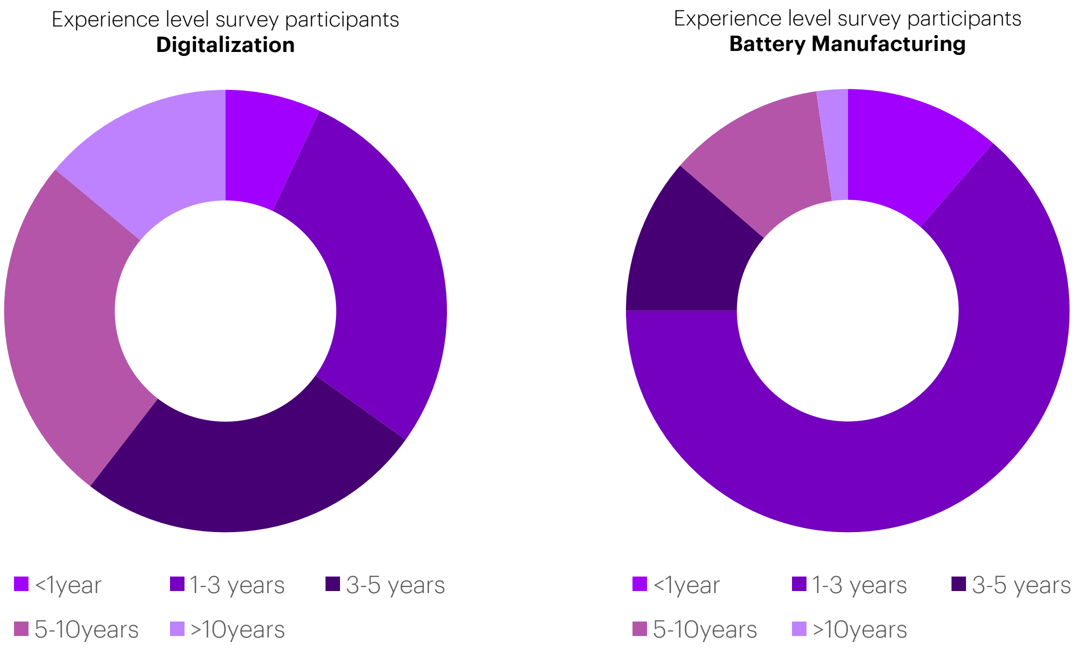


Figure 10: Distribution of experience level. The survey participants were asked to give their experience level in the field of digitalization and battery cell manufacturing.

		UC1 Predictive Quality (n=10) Mean*	Deviation	UC2 Predictive Maintenance (n=6) Mean*	Deviation	UC3 Virtual comissioning (n=6) Mean*	Deviation	UC4 Digital production planning (n=7) Mean*	Deviation
Energy Consumption	Mixing	2,7%		0,0%		3,8%		0,0%	
	Coating & Drying	8,3%		0,0%		6,3%		4,2%	
	Calendering	1,3%		0,0%		3,8%		0,0%	
	Slitting	1,2%		0,0%		2,5%		0,0%	
	Vacuum Drying	2,5%		0,0%		5,0%		0,6%	
	Separating	0,0%		0,0%		1,3%		0,0%	
	Stacking	0,0%		0,0%		0,0%		0,0%	
	Contacting	0,0%		0,0%		0,0%		0,0%	
	Closing	0,0%		0,0%		0,0%		0,0%	
	Electrolyte Filling	0,0%		0,0%		0,0%		0,0%	
	Formation	10,0%		0,0%		2,5%		1,8%	
	Aging	4,7%		0,0%		2,5%		0,6%	
	Testing	3,3%		0,0%		0,0%		0,0%	
Maintenance/-Downtime	Mixing	0,0%		11,3%		7,5%		7,0%	
	Coating & Drying	0,0%		17,8%		7,5%		6,2%	
	Calendering	0,0%		7,0%		7,5%		5,8%	
	Slitting	0,0%		12,5%		7,5%		4,2%	
	Vacuum Drying	0,0%		4,0%		3,8%		5,2%	
	Separating	0,0%		8,0%		0,0%		8,4%	
	Stacking	0,8%		3,0%		0,0%		9,6%	
	Contacting	0,8%		2,3%		0,0%		6,4%	
	Closing	0,0%		2,8%		0,0%		3,2%	
	Electrolyte Filling	0,8%		3,3%		0,0%		5,8%	
	Formation	0,0%		3,0%		2,5%		6,0%	
	Aging	0,0%		0,5%		1,3%		5,0%	
	Testing	0,0%		1,8%		0,0%		5,8%	
Scrap Rate	Mixing	3,3%		1,3%		5,0%		5,0%	
	Coating & Drying	11,2%		1,3%		5,0%		5,0%	
	Calendering	8,8%		1,3%		2,5%		0,0%	
	Slitting	2,5%		1,0%		2,5%		0,0%	
	Vacuum Drying	0,8%		0,0%		1,3%		0,0%	
	Separating	1,2%		0,0%		2,5%		0,0%	
	Stacking	4,2%		0,0%		1,3%		0,0%	
	Contacting	0,8%		0,0%		1,3%		0,0%	
	Closing	1,2%		0,0%		1,3%		0,0%	
	Electrolyte Filling	2,5%		0,0%		2,5%		0,0%	
	Formation	5,7%		0,0%		3,8%		0,0%	
	Aging	0,8%		0,0%		3,8%		0,0%	
	Testing	1,5%		0,0%		3,8%		0,0%	
Required Staff	Mixing	0,0%		0,0%		4,0%		1,4%	
	Coating & Drying	0,0%		0,0%		4,0%		1,0%	
	Calendering	0,0%		0,0%		3,8%		1,0%	
	Slitting	0,0%		0,0%		3,8%		0,0%	
	Vacuum Drying	0,0%		0,0%		1,3%		0,0%	
	Separating	0,0%		0,0%		2,8%		0,0%	
	Stacking	0,0%		0,0%		2,8%		0,8%	
	Contacting	0,0%		0,0%		2,5%		0,6%	
	Closing	0,0%		0,0%		2,5%		0,0%	
	Electrolyte Filling	0,0%		0,0%		2,8%		1,4%	
	Formation	0,0%		0,0%		1,8%		0,0%	
	Aging	0,0%		0,0%		1,3%		0,0%	
	Testing	0,0%		0,0%		2,5%		2,2%	

Standard Deviation
- 20%-25%
- 15%-20%
- 10%-15%
- 5%-10%
- <=5%

n = Number of full data sets
*Truncated mean (Aplha=0,4)

Figure 11: Survey results UC1-4. Note that 6-10 out of the total of 63 expert participants felt confident enough provide qualified input for all production steps.

		UC5	n=10	UC6	n=10	UC7	n=6
		Material flow simulation/ optimization Mean*	Deviation	**Traceability** Mean*	Deviation	**Energy tracking and optimization** Mean*	Deviation
Energy Consumption	Mixing	0,0%	◕	0,0%	●	8,5%	●
	Coating & Drying	0,0%	◑	0,0%	◔	20,0%	◕
	Calendering	0,0%	◕	0,0%	●	5,0%	●
	Slitting	0,0%	●	0,0%	●	4,5%	●
	Vacuum Drying	0,0%	◕	0,0%	○	18,0%	◕
	Separating	0,0%	●	0,0%	●	0,7%	●
	Stacking	0,0%	◕	0,0%	●	0,7%	◕
	Contacting	0,0%	●	0,0%	●	0,7%	●
	Closing	0,0%	●	0,0%	●	0,7%	●
	Electrolyte Filling	0,0%	◕	0,0%	●	0,7%	◕
	Formation	1,7%	◑	0,0%	●	12,5%	◔
	Aging	0,0%	◑	0,0%	●	2,3%	●
	Testing	0,8%	◕	0,0%	●	1,3%	●
Maintenance/-Downtime	Mixing	6,5%	◕	3,3%	◑	0,0%	●
	Coating & Drying	6,7%	◕	3,3%	◑	0,0%	●
	Calendering	5,0%	◕	3,3%	◑	0,0%	●
	Slitting	4,8%	●	3,3%	○	0,0%	●
	Vacuum Drying	5,3%	◕	0,0%	◕	0,0%	●
	Separating	3,2%	◕	0,0%	◕	0,0%	●
	Stacking	6,5%	◕	0,0%	◕	0,0%	◕
	Contacting	3,0%	●	0,0%	◕	0,0%	●
	Closing	3,7%	●	0,0%	◕	0,0%	●
	Electrolyte Filling	4,2%	◕	0,0%	◔	0,0%	●
	Formation	2,8%	◕	0,0%	◕	0,0%	●
	Aging	2,3%	◑	0,0%	◕	0,0%	●
	Testing	3,0%	◕	0,0%	◕	0,0%	●
Scrap Rate	Mixing	0,5%	◕	9,2%	◕	0,0%	●
	Coating & Drying	1,5%	◕	12,7%	○	0,0%	●
	Calendering	1,7%	◕	11,5%	◔	0,0%	●
	Slitting	1,3%	◕	8,7%	◕	0,0%	●
	Vacuum Drying	0,8%	●	5,0%	◕	0,0%	●
	Separating	0,0%	◕	4,3%	◑	0,0%	●
	Stacking	0,0%	●	12,5%	◑	0,0%	●
	Contacting	0,0%	●	3,8%	◕	0,0%	●
	Closing	0,0%	●	4,2%	◕	0,0%	●
	Electrolyte Filling	0,0%	◕	9,5%	◑	0,0%	◕
	Formation	0,0%	◕	11,3%	◔	0,0%	●
	Aging	0,0%	●	8,2%	○	0,0%	●
	Testing	0,0%	●	6,7%	◕	0,0%	●
Required Staff	Mixing	6,8%	◕	0,0%	●	0,0%	●
	Coating & Drying	7,0%	◕	0,8%	●	0,0%	●
	Calendering	5,7%	◕	0,8%	●	0,0%	●
	Slitting	6,3%	◕	0,8%	●	0,0%	●
	Vacuum Drying	6,0%	◕	0,8%	●	0,0%	●
	Separating	2,8%	◕	0,0%	●	0,0%	●
	Stacking	4,0%	◕	0,0%	●	0,0%	●
	Contacting	4,5%	◕	0,0%	●	0,0%	●
	Closing	3,7%	◕	0,0%	●	0,0%	●
	Electrolyte Filling	4,3%	◕	0,0%	●	0,0%	●
	Formation	3,5%	◕	0,0%	●	0,0%	●
	Aging	1,8%	◕	0,0%	◕	0,0%	●
	Testing	3,0%	◕	0,0%	◕	0,0%	●

Standard Deviation

- ○ 20%-25%
- ◔ 15%-20%
- ◑ 10%-15%
- ◕ 5%-10%
- ● <=5%

n= Number of full data sets

*Truncated mean (Aplha=0,4)

Figure 12: Survey results UC5-7. Note that 6-10 out of the total of 63 expert participants felt confident enough provide qualified input for all production steps.

Expenditure Scaling

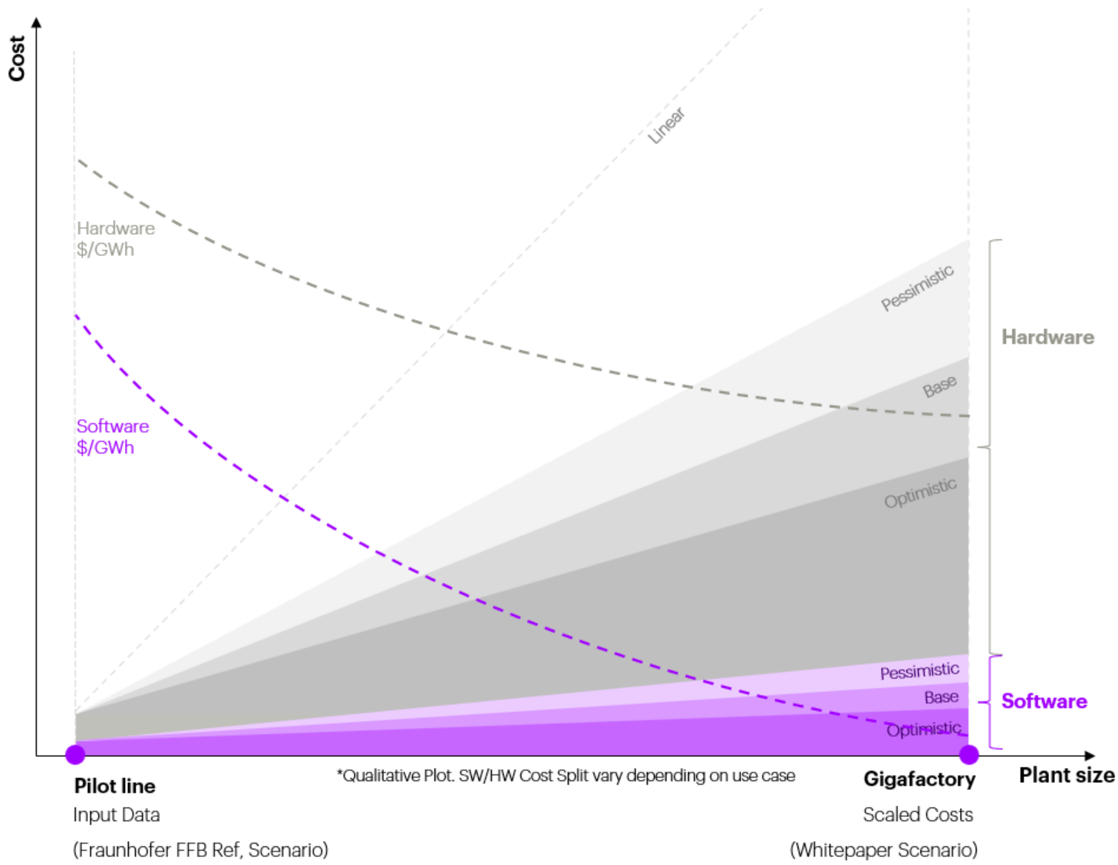


Figure 13: Qualitative illustration of hardware and software cost degression and consideration of different scenarios (optimistic, base case, pessimistic) for upscaling of cost depending on the plant size from 200 MWh/a to 40 GWh/a.

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Glossary

5G	5G is the fifth generation of cellular network technology, offering faster speeds, lower latency, and greater capacity than its predecessor, 4G, enabling more connected devices and advanced applications in various sectors.
AGV	Automated Guided Vehicles are self-propelled, driverless mobile robots designed for material handling and transportation tasks within a controlled environment.
AI	Artificial Intelligence – A branch of computer science that attempts to transfer human learning and thinking to computers. AI programs are self-learning and self-optimizing.
APS	Advanced Planning and Scheduling.
AR	Augmented Reality – Technology in which computer-generated images are superimposed on the real world. You see the real world and receive additional information through digital images.
BIM	Building Information Modeling – Cooperative working method that enriches and stores digital models of a building with relevant information. Once the building has been handed over, all partners are able to view the relevant information and continue working with it.
CAPEX	Capital Expenditure (CapEx) refers to single investments used by a company to acquire, upgrade, and maintain physical assets such as property, industrial buildings, or equipment.
CFD	Computational Fluid Dynamics is used for simulation by means of numerical fluid mechanics.
Cloud Computing	Computing system resources, notably data storage (known as cloud storage) and processing capabilities, on an as-needed basis, without the necessity for management by the user.
Computer Vision	Computer Vision is a sub-field of AI that enables computers to interpret and understand visual information from the world around them, essentially allowing them to see and process images and videos in a manner similar to human vision.
Data Lake	A data lake is a centralized repository that allows for the storage of vast amounts of raw data in its native format until it is needed, supporting the storage, processing, and analysis of data from multiple sources.
DBMS	A Database Management System (DBMS) is software that provides an interface for the storage, retrieval, management, and manipulation of data in databases, ensuring data integrity, security, and efficiency.
DPP	A Digital Product Passport (DPP) is a digital document that provides detailed information about a product's origin, materials, environmental impact, and recycling instructions, aimed at enhancing transparency and sustainability throughout its lifecycle.
DT	Digital Twins (DTs) are digital representation of a physically existing entity. At Fraunhofer FFB divided into machines, products, and buildings digital twin. Connection point for services and supplementary simulations.
Edge PC	Decentralized data processing at the edge of the network (Edge). Complementary to the cloud solution in the Fraunhofer FFB. Edge PCs are small, powerful computers in production that perform important tasks such as data acquisition and the execution of ML algorithms.
EPC	Engineering, procurement, construction.
ERP-System	Enterprise Resource Planning - Software solution for the resource planning of a company, which primarily includes finance, human resources, production, logistics, services and procurement. This is where high-level decisions are made that affect the entire company. In contrast to MES, ERP is also concerned with costs. The ERP from SAP is considered an integrated standard business software product.
GPU	A Graphics Processing Unit (GPU) is a specialized electronic circuit designed to rapidly manipulate and alter memory to accelerate the creation of images in a frame buffer intended for output to a display device. GPUs are crucial for AI due to their ability to perform parallel processing, significantly accelerating complex computations required for training and running deep learning models, thus enabling more efficient and faster development of AI applications.
Historian	In the context of industrial automation, a historian is a database software system designed to collect, store, and retrieve time-stamped data records and events for analysis, monitoring, and reporting of process operations over time.
HMI	A Human-Machine Interface (HMI) is a platform which provides the tools and interfaces for human operators to interact with and monitor automated systems, machinery, and processes, facilitating control and data exchange in industrial environments.
IoT	Internet of Things – Network of physical objects equipped with sensors, software and other technology. These objects are networked via the internet and communicate with each other.

IIoT-Platforms	Industrial Internet of Things Platforms - networks physical and virtual systems with each other on the basis of its own information and communication technologies. It uses online analytical processing and data mining to analyze and process all of a company's data in such a way that it can be used for decision-making. (e.g. through hidden patterns, correlations, market trends and customer preferences).
LIMS	Laboratory information management system.
KPI	Key Performance Indicator are measurable values that help to assess and track the progress toward specific business objectives.
MES	Manufacturing Execution System - is a computerized system used in manufacturing to track and document, for example, the conversion of raw materials into finished products. MES systems work in real time and enable the active control of several elements of the production process (e.g. inputs, personnel, machines and supporting services). They are therefore used for active and operational production control.
ML	Machine Learning – Sub-area of AI. ML uses algorithms and statistical methods to analyze data and identify patterns.
NMC	Lithium nickel manganese cobalt oxide is a commonly used cathode material.
OEE	Overall Equipment Effectiveness is a metric used to evaluate the efficiency of manufacturing processes by assessing the availability, performance, and quality of the equipment.
Ontologies/ Information Models	'Explicit formal specification of a common conceptualization' – Conceptual data model that is readably understandable and abstracted from all implementation-specific details.
OPC UA	Open Platform Communications Unified Architecture – Communication standard for Industry 4.0 and the IoT. Cross-company standardization of machine and system data enables manufacturer-independent data exchange.
OPEX	Operating Expense (OpEx) refers to the ongoing costs for running a product, business, or system, including salaries, rent, utilities, and maintenance expenses, but excluding capital expenditures.
Parameter List	A parameter list is a systematically defined set of variables or factors used to study and analyze systems or processes
Plant Simulation	Software for simulation, analysis, visualization and optimization of production processes, material flow and logistical processes
PLC	Programmable Logic Controller – programmable digital component in industrial environments for the control and regulation of systems and machines.
PLM	Product Lifecycle Management (PLM) is a strategic approach that uses software to manage a product's lifecycle from inception through design and manufacture to service and disposal, enhancing efficiency, product quality, and collaboration.
QMS	A Quality Management System (QMS) is a formalized system that documents processes, procedures, and responsibilities for achieving quality policies and objectives, aiming to enhance customer satisfaction and continuous improvement of operational efficiency.
Retrofitting	Retrofitting involves updating or adding new technology or features to existing systems, buildings, or machinery, to improve efficiency, performance, or compliance with current standards without completely replacing them.
RGM	Revenue Growth Management (RGM) is a strategic approach focused on driving revenue growth through pricing, promotion, assortment optimization, and distribution strategies, tailored to consumer demand and market dynamics.
SCADA-System	Supervisory Control and Data Acquisition – System that is located between the MES and the store floor. Used to connect and control systems across locations and to record data. Basic functions of an IIoT platform, but limited.
Shopfloor	The local area of a workshop / manufacturing / production.
Soft Sensors	Soft sensors are virtual sensors that use mathematical models and algorithms to infer the value of a parameter from the measurement of other physical variables, enabling indirect monitoring and control in various applications where direct measurement is challenging.
Traceability System	A traceability system contains the information about the workpiece carriers and checks the accuracy of the materials on the workpiece carriers.
VR	Virtual Reality – Technology in which the real world is replaced by a digital environment

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About Accenture

Accenture is a leading global professional services company that helps the world's leading businesses, governments and other organizations build their digital core, optimize their operations, accelerate revenue growth and enhance citizen services—creating tangible value at speed and scale. We are a talent- and innovation-led company with approximately 733,000 people serving clients in more than 120 countries. Technology is at the core of change today, and we are one of the world's leaders in helping drive that change, with strong ecosystem relationships. We combine our strength in technology and leadership in cloud, data and AI with unmatched industry experience, functional expertise and global delivery capability. We are uniquely able to deliver tangible outcomes because of our broad range of services, solutions and assets across Strategy & Consulting, Technology, Operations, Industry X and Song. These capabilities, together with our culture of shared success and commitment to creating 360° value, enable us to help our clients reinvent and build trusted, lasting relationships. We measure our success by the 360° value we create for our clients, each other, our shareholders, partners and communities.

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We use the synergies of data and digitalization to rethink products and manufacturing processes. We call this integrated approach to digital engineering and manufacturing 'Industry X'. We work with you to make your core processes more resilient, productive and sustainable. The basis is formed by technologies such as AR/VR, cloud, AI, 5G, robotics and digital twins. Digital intelligence connects all points of the value chain. This is how we create hyper-personalized experiences as well as intelligent products and services. Industry X digitizes all areas of your company. We work with you to rethink how products and services are developed and designed, procured and delivered, manufactured and maintained, returned and renewed.

Fraunhofer Research Institution for Battery Cell Production FFB

As a link between science, research, and industry, the main objective of the Fraunhofer Research Institution for Battery Cell Production FFB is to establish a research infrastructure for an ecological and economical battery cell production. The intention is to accelerate the innovation and commercialization process of production technologies for existing and future cell formats. The focus is on all areas relating to battery production: from battery technology and certification of new battery types to process optimization in production, application, battery recycling, and further education opportunities.

Fraunhofer FFB addresses companies from the mechanical and plant engineering and cell production sectors, as well as integrators of lithium-ion battery cells, who wish to further develop their products based on the latest cell technologies. In this European center, which brings together leading experts in German battery and production technology from industry and research, the Fraunhofer FFB is working on the transfer of new battery concepts and production technology from prototype to series production.

With a strong basis in battery cell production research and innovative plant technology, the Fraunhofer FFB is creating the conditions for large-scale production. The work focuses on the latest requirements and standards for industrial battery cell production. In this way, the Fraunhofer FFB creates the conditions for scaling innovations at the product and process level to a high standard.

Why we teamed up

The collaboration between Fraunhofer FFB and Accenture for this Whitepaper is a partnership that reflects the capabilities of both organizations.

Fraunhofer FFB, with its strong focus on advancing battery cell production technology and its application in industry, provides crucial insights into the technical and process-specific aspects of battery manufacturing. This includes research on battery technology, optimization of production processes, and the scaling of innovations in battery cell production, ensuring adherence to the latest industrial standards and quality criteria.

Accenture Industry X brings to the table its extensive expertise in digital transformation across engineering, manufacturing, and operational processes. The firm's capabilities in digital technologies are instrumental in reimagining and digitizing the manufacturing value chain.

By integrating these digital capabilities with Fraunhofer FFB's technical and process knowledge, the partnership aims to creates a robust platform for exploring the digital potentials in battery cell manufacturing.