Master's Thesis
Joint Master in Decentralized Smart Energy Systems

A Methodology for End-to-End Digitalization of Battery Cell Production

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Abstract

Due to their high energy density, long life cycle and shelf life, lithium-ion batteries (LIBs) play a decisive role in the successful electrification of vehicles. In fact, the largest automotive companies worldwide currently bet on LIBs to reach their sustainability targets within the next decades. From 2026 on, EU regulations mandate that a digital passport comprising technical information and data related to their environmental performance be attached to all EV batteries. Meeting the sustainability targets and complying with the battery passport regulation require the digital transformation of the LIB manufacturing industry. This thesis proposes a novel methodology to digitalize complex manufacturing processes such as battery cell production from data creation to data storage and tackle limitations to successful implementation of data analytics such as lack of data acquisition, poor data quality and scarcity of usable data. The methodology for industrial digitalization of complex processes (MIDCOP) accounts for the complexity, scalability, cybersecurity, data quality requirements of manufacturing processes and outlines an enabling data integration strategy. MIDCOP perfectly fits the digital transformation of battery cell production which can benefit from data-driven solutions to address current inefficiencies in the production (high scrap rate that leads to significant C02 emission) and generate relevant data needed to create the digital passport. The application of the methodology to the electrode manufacturing process, in particular to the mixing step, proves how effectively it can integrate diverse conceptual and technical criteria to enable an end-to-end digitalization of the entire battery cell production process.

Keywords
Battery Cell Production, Complex Manufacturing Process, Data Analytics,
Data Engineering, Digitalization, IoT, OPC UA

Context

This thesis originates from an internship conducted at BMW Group's Battery Cell Competence Center (BCCC), located in Munich. The BCCC was established in 2019 with the primary objective of developing new battery cells, manufacturing them on a prototype scale, and conducting extensive testing[1].

The main focus of the internship has been to support the digitalization efforts of the Cell Manufacturing Competence Center (CCMC). The CCMC operates a near-standard production pilot line situated in Parsdorf (in the outskirts of Munich) and commissioned in 2022[2], which serves as a demonstration of the BMW Group's ability to industrially produce future generations of high-performance battery cells (Figure 9.1). This pilot line enables the thorough analysis and comprehensive understanding of cell value creation processes. The initial development phase, with an investment of 170 million euros, is dedicated to exploring innovative production processes and systems that can eventually be integrated into standard production[3].

The digitalization efforts for the entire pilot line involve establishing connectivity among all machines on the factory floor. The IoT Team which I joined is, therefore, responsible for designing and implementing a data integration strategy that encompasses data acquisition, transport, transformation, storage, and visualization. The goal is to ensure seamless flow of information and enable data-driven decision-making throughout the production line.

[1] https://www.electrive.com/2019/11/14/bmw-opens-battery-competence-centre-in-munich/

[2] https://www.press.bmwgroup.com/portugal/article/detail/T0406680PT/%E2%80%9Cbuilding-the-future-of-electromobility-right-here%E2%80%9D:-commissioning-gets-underway-at-bmw-group-cell-manufacturing-competence-centre

[3] https://www.press.bmwgroup.com/global/article/detail/T0392453EN/bmw-group-to-open-cell-manufacturing-competence-centre-this-autumn?language=en

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Abbreviations

BCCC	Battery Cell Competence Center
BEV	Battery Electric Vehicle
BI	Business Intelligence
CMCC	Cell Manufacturing Competence Center
CO2	Carbon Dioxide
EV	Electric Vehicle
GWh	GigaWatt-hour
HMI	Human Machine Interface
IoT	Internet-of-Things
LCA	Life Cycle Assessment
LIB	Lithium-Ion Battery
LMT	Lightweight Means of Transport
MIDCOP	Methodology for Industrial Digitalization of COmplex Processes
OEM	Original Equipment Manufacturer
OPC UA	Open Platform Communications United Architecture
PLC	Programmable Logic Controller
SIPOC	Suppliers, Inputs, Processes, Outputs and Customers
TCP/IP	Transmission Control Protocol/Internet Protocol
WEF	World Economic Forum

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Chapter 1

Introduction

1.1 Motivation

Currently, the transport sector accounts for 23% of all C02 emissions. Yet, estimates suggest that the global vehicle fleet will double at the horizon 2050 [1]. To stay on track with the Paris Agreement goals, reduce air pollution and dependence on fossil fuel, the transport sector must rapidly shift towards electric vehicles, bikes and transit. On that front, considerable effort to advance sustainable mobility is noticeable worldwide. The International Energy Agency (IEA) describes a bright outlook for growth in electric vehicles as global sales surpassed 10 million in 2022 [2]. Other reports project more than 30 million zero-emission EVs in Europe by 2030 [3]. This expected growth in electromobility occasions a rapid increase in the demand for battery manufacturing capacity. In fact, recent studies [4] anticipate that the global demand for Li-ion batteries will expand from 700 GWh in 2022 to 4.7 TWh by 2030, generating a market value above $400 billion. In Europe alone, due to technical breakthroughs and a favorable political context[1], battery cell manufacturing is poised to increase 50 fold from 25 GWh production volume in 2020 to 1,300 GWh in 2030 [5].

As government subsidies and forecasts of a booming market demand drive the planning and construction of battery gigafactories across Europe[2], appropriate measures must be taken to ensure the sustainability and transparency of the battery production activities. In fact, in 2020, the European Union introduced a new Battery Regulation[3] with the aim of shaping a more efficient battery industry,

[1] EU's initiatives to support battery manufacturing

- Fit for 55 program
- 2035 ban of internal combustion engine (ICE) vehicles

[2] Battery cell production in Europe per country and per company. See https://battery-news.de/index.php/2023/02/03/16260/

[3] The new regulation proposed on 10th December 2020 is expected to be published in May

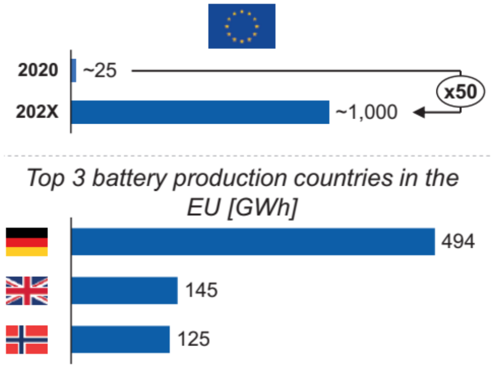

Figure 1.1: Growth rate of European battery production capacity [GWh] [5]

boosting the circularity of the production chain and creating more competition in the european market[4]. The new EU Battery Regulation requires that enough data be gathered from all the stakeholders of the battery ecosystem (miners, cell producers, module producers, battery pack producers, distributers, automotive OEMs, end-of-life treatmemt providers[6]) to ensure the traceability, sustainability and safety of the batteries. Specifically, all electric vehicle batteries, industrial batteries with internal storage exceeding 2kWh and lightweight means of transport batteries (LMT)[5] must contain a Digital Battery Passport (applicable to all EU members by 1 January 2026). The said passport is expected to include key information about the life cycle of the battery and be physically attached to the battery as a QR-Code. The information needed comprises battery model data and individual battery usage data[6], [7]; Figure 1.2 shows the explicit information requirements for the new battery regulation.

To comply with the new regulations, all the stakeholders of the battery ecosystem need to transition to digital transformation solutions. In particular, battery cell production which involves complex operations, with multiple stages and numerous parameters can benefit greatly from digitalization. By leveraging digital technologies, manufacturers can improve the efficiency, quality, and consistency of the production. Furthermore, battery cell production faces specific challenges in terms of traceability. Traceability refers to the ability to track and record the origin, history, and movement of components and materials throughout the manufacturing process. Traceability not only ensures compliance with the regulations and standards mentioned above but also helps in identifying and resolving poten-

2023 https://www.flashbattery.tech/en/new-european-battery-regulation/

[4]https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020PC0798

[5]e-bikes, electric scooters

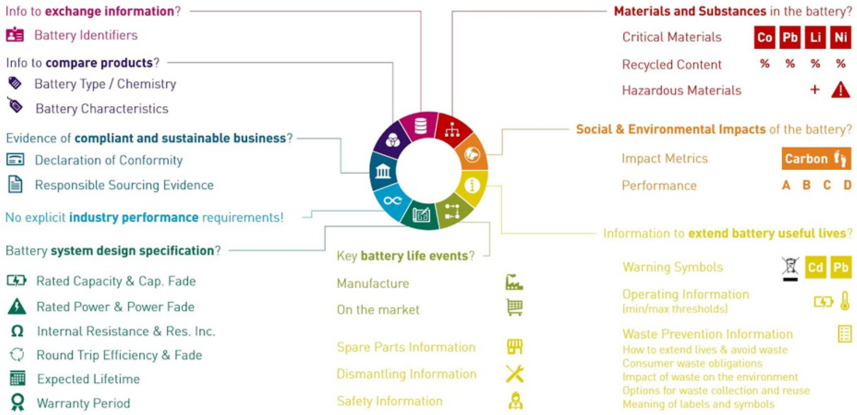

Figure 1.2: Explicit information requirements for EU battery regulation [8]

tial issues or defects, allowing for timely interventions and minimizing the impact on product quality. Achieving effective traceability in battery cell production can be challenging due to the complexity of the supply chain, the presence of diverse stakeholders, and the need to monitor countless critical parameters.

Digital transformation entails the abandon of legacy manufacturing systems to adopt data-driven approaches. Additionally, digitalization enables real-time data collection, analysis, and process optimization, allowing manufacturers to gain deep insights into each step of the production process. Therefore, by providing comprehensive record-keeping and enabling accurate traceability throughout the battery cell production process, digitalization can tackle the described complexities and help meet the new battery regulations.

While mature scientific approaches leading to more sustainable LIBs exist, researchers and industry leaders alike are still investigating suitable methodologies to digitally transform complex manufacturing processes and generate accurate, complete & usable data.

1.2 Objective & Approach

Acknowledging the need for comprehensive data collection throughout the battery cell production, this thesis aims to propose a methodology for the digitalization of complex manufacturing processes, with a case study focusing on battery electrode manufacturing. The said methodology should encompass the entire data lifecycle, from data acquisition to data storage, ensuring the availability of accurate and relevant data for analysis and decision-making. Additionally, the work intends to specify the key stakeholders involved in the digital transformation of a given factory, clarifying their respective responsibilities in facilitating seamless implementation of the proposed methodology. By addressing the challenges of data acquisition and scarcity of usable data, this research work will provide valuable insights and practical solutions for both academic researchers and industry practitioners.

The present thesis contains 8 chapters outlined as follows:

- **Chapter 2: Battery Cell Production and IoT** provides an overview of the battery cell manufacturing process to highlight its digitalization requirements, challenges and showcase potential benefits of a successful digitalization of such complex process.
- **Chapter 3: State of the Art** presents the existing methodologies and frameworks for digitalization and points out their limitations with regard to complex manufacturing processes. A research gap is also identified and serves as basis for the formulation of the research questions.
- **Chapter 4: Proposed Methodology** describes in detail the novel methodology for industrial digitalization of complex processes.
- **Chapter 5: Case Study** applies the proposed methodology to the battery electrode manufacturing process, in particular to the mixing step.
- **Chapter 6: Discussion** includes a critical analysis of the proposed methodology with a focus on how well it covers the conceptual and technical criteria for successful digitalization of complex processes. The socio-economic and environmental impacts of the implementation of the digitalization strategy are also discussed.
- **Chapter 7: Conclusions & Chapter 8: Future Work** draw conclusions from the research findings, highlight the key insights and contributions to the field of digitalization. Additionally, potential avenues for future work and research are discussed, offering opportunities to expand upon the findings of this thesis.

Chapter 2

Battery Cell Production and IoT

This chapter provides additional context to the digitalization of manufacturing processes such as battery cell production, showing that their complexity, and traceability needs call for a digital transformation. The enabling tech stack is also introduced.

2.1 Battery cell production

2.1.1 Production process

The production process of battery cells encompasses several stages [9], [10]. It begins with the preparation of raw materials, including active materials, binders, and electrolytes. These components are meticulously mixed and coated onto current collectors, which are then dried and rolled to form electrode sheets. During cell assembly, the electrode coils enter a dry room where they are cut into individual sheets. These sheets are wound and securely joined through ultrasonic welding. The assembled cells are then housed in cans, and the electrolyte is added to complete the filling process. The cells undergo a formation step within a controlled chamber, where they are subjected to specific climatic conditions and quality evaluation for several days. Prior to packaging and shipment, the completed cells undergo testing and quality control measures to ensure their reliability and performance.

Figure 2.1 illustrates the sequential steps of the battery cell production process.

2.1.2 Key processes in electrode manufacturing

Some authors consider electrode manufacturing as the core step in the production of battery cells, as it establishes crucial properties that directly impact the electrochemical performance of the cells [12]. This phase also involves a multitude of

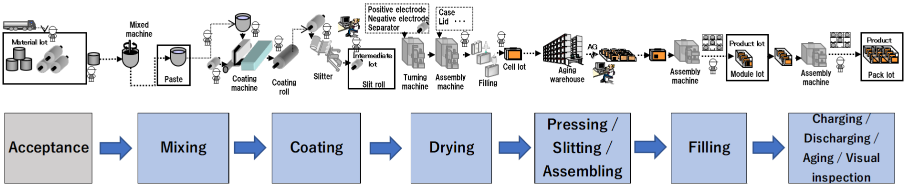

Figure 2.1: The various steps of the battery cell manufacturing process with their respective specialized machine [11]

product and process parameters that exhibit strong interdependencies, resulting in a highly complex manufacturing process.

The electrode manufacturing begins with dry mixing, creating a uniform mixture of electrode materials and breaking down carbon black agglomerates. High-energy mixing devices such as intensive or annular gap mixers are used for this purpose. Wet mixing follows, adding solvent to the dry materials to form electrode slurry, ensuring proper wetting and binder solubility (Figure 2.2). The size and distribution of the carbon black aggregates in the slurry significantly impact electrical and ionic conductivity. Wet mixing parameters influence material distribution, slurry homogeneity, and subsequent mechanical and electrochemical properties [13], [14].

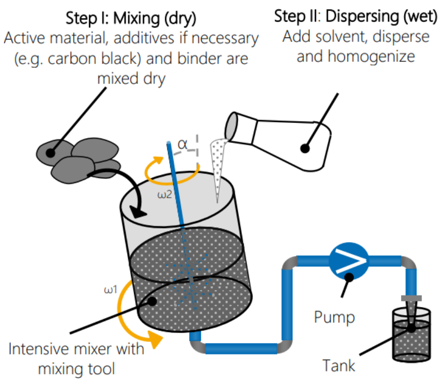

Figure 2.2: Overview of the mixing process [13]

Next, the coating process involves using a technique called slot-die coating. This method applies the electrode slurry onto the current collector substrate in a controlled and uniform manner. The slot die guides the slurry onto the substrate, creating a consistent coating width (Figure 2.3). The flow of the slurry is carefully regulated to determine the thickness of the coating across the substrate, taking into account the speed of the substrate for accurate results [13], [14].

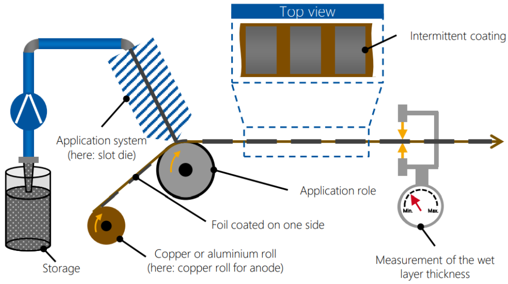

Figure 2.3: Overview of the coating process [13]

2.1.3 Complexity of battery cell production

The extensive process chain of battery cell production involves numerous interdependent steps as shown in Figure 2.1, effectively showcasing its complexity. Thiede et al. [9] have identified over 500 changeable process parameters and state variables, as well as 1029 intermediate product features and 65 final product properties, which collectively characterize the production process. A subset of the list of critical parameters monitored in the mixing process is presented in Table 5.1. Collecting data from these parameters at a high frequency, such as every 100 ms, can easily generate data volumes amounting to several hundred gigabytes per day of operation[1].

Other studies reveal that electrode manufacturing influences around half (51.7%) of the total parameters in battery cell production. Since defects in the early stages of the production can propagate throughout the process chain, leading to increased scrap rates, this large number of parameters is necessary to closely monitor and meet electrode quality standards. The mixing step alone accounts for 23% of the total parameters, reflecting the comprehensive evaluation of raw material quality within the slurry that impacts the overall quality of battery cells [15]. Mixing and coating together claim more than 39% of the parameters needed (Figure 2.4).

Beside the large number of parameters and volume of data to be processed, the unknown cause-effect relationships between these parameters, intermediate products & processes, and quality characteristics add to the complexity of the battery cell production process [16].

Furthermore, the production of batteries faces challenges in terms of high scrap rates and, consequently, demands significant efforts for quality control. While determining the exact scrap rates for battery companies is difficult, estimates

[1] Estimate for a unity-scale battery factory

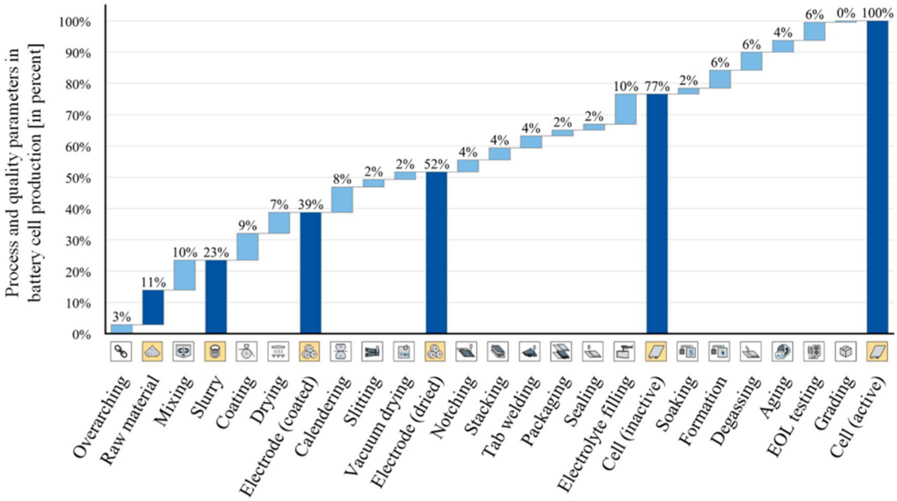

Figure 2.4: Relative distribution of parameters along the battery cell production chain [15]

suggest that they can reach as high as 30% during battery prototyping. The best lithium-ion battery producers experience around 5% of scrap rates, typical producers 10%, and start-up phases potentially witness rates of 30% or even higher [17], [18]. The mixing and coating processes that account for the larger share of the necessary parameters also tend to create the most rejects as depicted in Figure 2.5.

According to Haghi et al. [12], a detailed understanding of all the battery cell production steps, their interrelationships, and the early identification of scrap in the initial stages of the production chain can greatly diminish the overall scrap rate.

Lastly, traceability is essential in battery cell manufacturing for quality control. It involves reviewing the product history throughout the manufacturing chain, enabling precise data mapping. This system serves as the foundation for various applications, from analyzing production processes to optimizing energy demand. However, developing a traceability solution with detailed data can be costly, especially in continuous process steps. Prioritizing parameters to track at the electrode manufacturing level (material IDs, slurry IDs, process names, electrode IDs, etc) becomes crucial [12]. To create a reliable traceability system in battery cell manufacturing, Kaus et al. [20] propose to also consider the speed and accessibility of sensor information, addressing missing process parameters and product characteristics, integrating additional sensors as needed, determining suitable sampling rates, and ensuring efficient data collection and management.

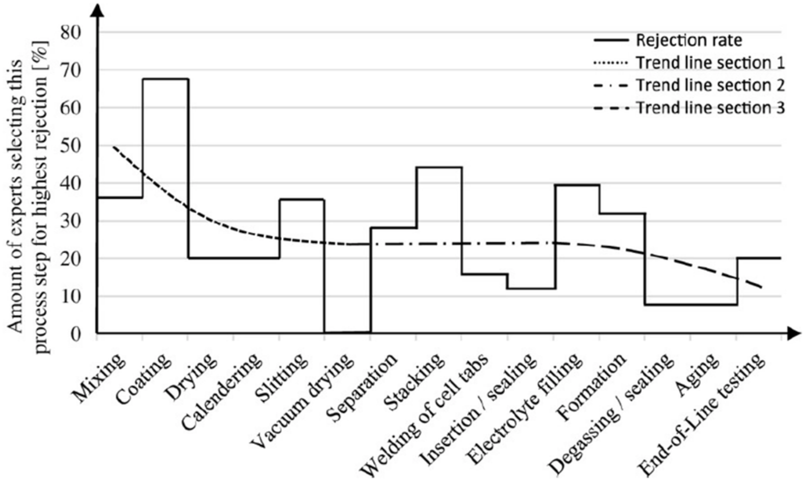

Figure 2.5: Processes that create the most rejects [19]

2.1.4 Machine commissioning and ramp up

Machine commissioning encompasses the installation, testing, and calibration of production machinery and equipment to ensure their proper functioning and compliance with required specifications. Additionally, it involves conducting trial runs, addressing any troubleshooting needs, and certifying that the machines are fully prepared for full-scale production. Since each machine is customized to meet the specific requirements and production lines of the battery cell producer, commissioning in the machines for battery production presents its difficulties. Utilizing data can help streamline the process by enabling more accurate analysis and evaluation of machine performance [21].

Production ramp-up in battery cell production refers to the gradual increase in production volume and capacity to meet market demands. It entails scaling up the manufacturing process from initial pilot or prototype production to full-scale production. Throughout the ramp-up phase, diverse activities take place, including the optimization of production lines, fine-tuning of process parameters, quality assurance and reliability checks for the battery cells. Ramping up machines for stack formation in battery cell production is challenging due to limited knowledge of cause-effect relationships. This applies to both initial setup and process input variable changes [22].

2.2 Digital transformation

2.2.1 End-to-end digitalization

Various definitions of digitalization exist in the literature. Wanner et al. [23] present digitalization as the conversion of information into a digital format. This information can originate from diverse sources, such as sensors or machines on a factory floor. By processing and utilizing this digital information, significant transformations can be achieved in a manufacturing process. For Haghi et al. [12], digitalization is the process of harnessing digital technologies and sensors to enable and enhance manufacturing processes. These authors suggest that the primary goal of digitalization is to facilitate the creation of transparency and enable a wider utilization of digitized data such as generation of actionable knowledge and business insights.

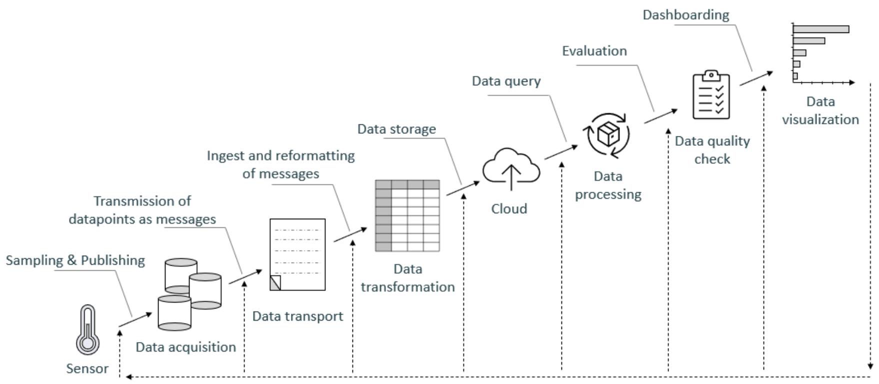

Figure 2.6: End-to-end digitalization

Within the scope of this work, end-to-end digitalization of complex manufacturing processes involves the systematic process of creating, acquiring, transporting, and storing data obtained from sensors deployed on the factory floor. The data is then stored in on-premise or cloud databases, and meaningful insights derived from it are visualized through dashboards. The various steps of the end-to-end digitalization as considered in this thesis are shown in Figure 2.6.

2.2.2 Enabling tech stack

Big data analytics is crucial for productivity, process safety, product quality, and the resilience of manufacturing systems in the smart factories era [24]. Industry 4.0 represents the transition from mechanization and automation to digitalization, introducing Smart Factories that are interconnected through Internet-of-Things

(IoT) and utilize cloud services [20]. IoT enables the deployment of smart sensors for real-time data capture, while cloud computing facilitates networked data collection, remote analytics, and efficient data handling. Artificial intelligence (AI) and machine learning (ML) enable flexible decision-making and support autonomous operations in big data analytics systems [24].

In the context of Industry 4.0, the digitalization of manufacturing systems has become a central focus. This transformative process involves adopting new data modeling practices and communication standards to enhance traditional systems. One such communication standard that plays a pivotal role in this paradigm shift is the Open Platform Communications - Unified Architecture (OPC-UA) [25]. OPC-UA provides a comprehensive framework for achieving a holistic understanding of the machines on the factory floor.

The OPC-UA standard has the potential to integrate equipment from different vendors and architectures, aligning with Industry 4.0 goals. It enables communication across all levels of manufacturing enterprises via TCP/IP protocols, facilitating data exchange beyond local networks. OPC-UA's information model captures the semantics of the physical system. In addition to data modeling, OPC-UA offers benefits in security, reliability, access control, alarm generation, and historical data provision [25].

The OPC-UA standard[2] employs a notation system that encompasses an information model consisting of nodes, which are exposed to clients through the address space. In the context of modeling machines on the factory floor, the prevalent notations utilized are "Object" and "Variable" nodes, alongside the "HasComponent" and "HasSubtype" reference notations. This approach facilitates the modeling of various machine types and their respective subcomponents. Additionally, this architecture proposes to divide the machines into segments and components in which each sensor/device represents a component that may include subcomponents and variables.

Moreover, cloud computing has revolutionized the digitalization of manufacturing processes by significantly enhancing computation and data storage capabilities. Through the utilization of cloud computing, the capacity to handle large volumes of data increases exponentially, allowing for seamless measurement and transmission of all pertinent production data to cloud storage platforms. Battery cells producers are currently leveraging the power of Industry 4.0 and cloud computing to benefit from advanced analytics & predictive models driving continuous improvement in battery cell production.

2.2.3 Challenges for the digitalization of complex processes

This chapter examines the inherent complexities of manufacturing processes, particularly in battery cell production. To ensure the success of any digitalization

[2]The OPC UA specifications: https://reference.opcfoundation.org/

initiative, it is crucial to consider and incorporate these key factors. They include a large amount of parameters and data, the need for traceability, machine connectivity, cybersecurity measures, flexibility and scalability, the challenge of identifying cause-effect relationships, comprehensive understanding of production steps, and the limitations in knowledge to speed up production ramp-up and machine commissioning. A digitalization methodology that acknowledges and addresses these properties can navigate the complexities of manufacturing processes more effectively.

Chapter 3

State of the Art

This chapter derives criteria for a succesful digitalization of complex manufacturing processes & surveys the existing academic literature, identifies research needs and specifies the research questions to be addressed.

3.1 Criteria for evaluation of existing digitalization methodologies

To assess recent digitalization methodologies for complex manufacturing processes such as battery cell production, it is important to evaluate their suitability based on conceptual and technical criteria. By considering the following criteria derived from the specificity of the complex manufacturing processes, a comprehensive framework can be established to benchmark the existing methodologies and determine their relevance for a successful digital transformation of battery cell production.

Conceptual Criteria	Technical Criteria
End-to-end digitalization	Interoperability
Scalability	Machine connectivity
Facilitation of fast commissioning	Cybersecurity
Enhancement of sustainable production	Big data
Accurate data modelling	Data storage
Automation degree of the data acquisition	Data quality check
	Business Intelligence (BI) dashboards

Table 3.1: Criteria for successful digitalization of complex manufacturing processes

Each of the criterion above-mentioned plays a different role in ensuring a successful digitalization of battery cell production:

On the conceptual side:

- End-to-end digitalization: Capturing and integrating data across all stages of the manufacturing process, from data acquisition to storage and analysis.
- Scalability: Capacity to accommodate growing production volumes and changing requirements without compromising performance or efficiency.
- Facilitation of fast commissioning: Reduction of the time required for manufacturers to transition from traditional to digital processes, minimizing downtime and accelerating the realization of benefits.
- Enhancement of sustainable production: Monitoring and optimization of environmental impacts by leveraging data-driven insights.
- Accurate data modeling: Representing manufacturing processes in a digital format taking into account the integrity, consistency and flexibility of the data models.
- Automation degree of data acquisition: Degree of real-time collection of data from various sources (sensors and IoT devices) minimizing manual intervention.

On the technical side:

- Interoperability: Integration between different systems, devices, and software of the manufacturing plant, facilitating data sharing and communication.
- Machine connectivity: Real-time data exchange and control of production machines and equipment with digital systems.
- Cybersecurity: Protection of digital systems, data, and intellectual property from unauthorized access.
- Big data: Large volumes of structured and unstructured data generated during the production process. Big data analytics can help identify patterns and valuable insights for process optimization.
- Data storage: Secure management of the vast amounts of data generated in battery cell production to ensure data availability, accessibility, and integrity for analysis.
- Data quality check: Verification of the accuracy, consistency, and reliability of the data to enable confident decision-making.

- Business Intelligence (BI) dashboards: Interactive dashboards that enable stakeholders to monitor key performance indicators, metrics, and trends derived from manufacturing data.

Manufacturers can create a solid foundation for a successful digital transformation in battery cell production by considering and addressing these conceptual and technical criteria.

3.2 Literature Review

The following literature review will aid in identifying any research gaps and further research needs in the field of digitalization for complex manufacturing processes. An overview of the findings is given in Table 3.3 based on the conceptual and technical criteria described in Table 3.1. Table 3.3 leverages the Harvey Balls[1] schema to visually compare the selected studies against the defined digitalization criteria. The degree of fulfillment of the said criteria ranges from 0 to 100% as shown in Table 3.2 and the evaluation relies on expert judgement.

Symbol	Interpretation
○	not fulfilled - criterion not mentioned
◔	low fulfillment - criterion only referred to
◑	medium fulfillment - criterion somewhat discussed
◕	high fulfillment - novel method proposed
●	complete fulfillment - main focus of the study

Table 3.2: Evaluation criteria of the existing studies on digitalization of manufacturing processes

Schnell et al [16] have demonstrated that data mining [2] methods including Generalized Linear Model (GLM), Random Forest (RF) and Gradient Boosted Trees (GBT) can assist to systematically analyze data acquired during the manufacturing processes of LIB. These methods contributed to determine quality drivers, predict cell quality and discover process interdependencies. Nevertheless, the study underlines a wide gap between available data and usable data[3] citing incomplete

[1] https://blog.minitab.com/en/harvey-balls-some-of-the-best-presenting-visual-comparisons-you-might-not-have-even-heard-of

[2] extraction and enumeration of patterns from data

[3] The available dataset comprises all the parameters collected over all process steps. Then, in the usable dataset, parameters related to scrap and rejects are discarded. Finally, the processible dataset results from data processing techniques such as data selection, data formatting, data integration, etc.

datasets, data loss in manual assembly processes, absence of critical sensors and inaccurate entries in the database due to user errors[16]. Well-known data mining methodologies such as CRISP-DM (CRoss-Industry Standard Process for Data Mining) and SEMMA (Sample, Explore, Modify, Model, Assess) consist of a series of iterative stages encompassing business & data understanding, data preparation & modelling to extract knowledge from a database. They do not, however, address the limitations to data acquisition raised by Schnell et al [16]. More generally, the data analytics algorithms cannot derive insights from process parameters that were not captured during the manufacturing process. These limitations to data mining call for a comprehensive methodology to collect data (process parameters, intermediate product attributes), store data and create complete datasets.

In an effort to extend CRISP-DM, Huber et al [26] propose the data mining methodology for engineering applications (DMME) including an additional data acquisition phase. The *Technical Implementation* stage of DMME defines a theoretical strategy to collect run-time data during production; the said strategy includes ensuring that the machine sensors are "capable of streaming data over a long period" and developing a "software infrastructure" to oversee the streaming data over long periods. While DMME provides relevant insights towards the digitalization of manufacturing processes, the methodology left important digitalization requirements such as a comprehensive workflow for the subtasks, interconnection of machines, data infrastructure and data quality check open for further investigations.

Han et al [27] address the challenge of interconnection and interoperability of equipment from different vendors on a battery cell production line by building a standardized and consistent OPC UA information model. This information model depends on the organizational structure, functional modules, and information flow of the given production plant. In their proposal to digitalize battery recycling, Kintscher et al [28] also identify information exchange between different actors of the supply chain as a key issue for the digital transformation of factories. These authors recommend to interconnect equipment via the platform-independent communication standard OPC UA in order to solve the lack of information in the recycling sector and handle the heterogeneity of machines/devices/robots. The methodologies developed by both Han et al [27] and Kintscher et al [28] showcase a high degree of automation of the entire data acquisition process, have the potential to model the manufacturing plant fairly accurately but lack a dedicated data infrastructure capable of streaming, storing and visualizing high-frequency data.

Kampker et al [15] explore the concept of a digital product twin of a battery cell which is a virtual replica of the physical battery (geometry, material properties, manufacturing history). The digital product twin aims at structuring the data collected from the production processes based on its own product architecture. Additionally, by incorporating data from intermediate products and subassemblies, the digital twin would allow for further modelisation and analytics work. To implement the digital twin, Kampker et al [15] propose to initially create an information model capturing relevant product data, then map data sources to data targets and finally transform the data to suitable data types. Nevertheless, the digital twin product approach fails to convey the need for interoperability, cybersecurity and reliable data architecture that arises in complex manufacturing processes.

Haghi et al [29] highlight that the data-driven approach (compared to expert-based and simulation-based) has merit in real-time application and deduction of unknown interdependencies in manufacturing processes. They introduce a digitalization framework applicable to electrode production to take advantage of the increasing amount of data created in the production systems. Even though the framework specifically contains a Tailored Digitalization Concept, it falls short of proposing a standard methodology to create datasets or an end-to-end digitalization strategy from data creation to data storage.

Overall, as shown in Table 3.3, diverse proposals for the digitalization of manufacturing processes exist. While several of these methodologies already account for the scalability of data collection and automation of the acquisition process, the literature still lacks a comprehensive digitalization methodology comprising data creation to data storage, contribution to fast commissioning and plant ramp-up, accurate data modelling and data quality check.

	Huber et al 2019 [26]	Han et al 2020 [27]	Kintscher et al 2020 [28]	Kampker et al 2023 [15]	Haghi et al 2021 [29]	Wanner et al 2021 [23]
	[26]	[27]	[28]	[15]	[29]	[23]
Conceptual Criteria						
End-to-end digitalization	◑	◔	◔	◑	◑	◑
Scalability	●	◑	◔	●	●	◑
Facilitate fast commissioning	◑	○	○	◑	◑	○
Enhance sustainable production	◕	○	●	●	◑	●
Accurate data modelling	◔	◑	◑	◔	○	○
Automation degree of the data acquisition	◑	●	●	◔	◔	●
Technical Criteria						
Interoperability	○	●	●	○	○	◑
Machine connectivity	○	●	●	○	○	◔
Cybersecurity	○	○	○	○	○	○
Big data	◑	○	◑	◑	◔	◔
Data storage	◔	○	○	○	○	◕
Data quality check	○	◕	○	◑	◑	○
User-friendly BI dashboards	○	◑	○	○	◑	○

Table 3.3: Overview of the literature study on digitalization of complex manufacturing processes

3.3 Research questions

Complex manufacturing processes such as battery cell production generate a significant amount of data that can be utilized for improved traceability, product quality control and sustainability. However, the literature review showcases that existing digitalization approaches fail to account for all the characteristics of complex manufacturing processes i.e. large amount of parameters, machines from different vendors, machine connectivity, cybesecurity and data quality control. Therefore, the objective of this thesis is to outline a comprehensive digitalization methodology incorporating the conceptual and technical criteria (Table 3.1) which tackles the existing gap in the scientific literature and allows for the creation of complete, accurate and secure datasets.

The following research questions have been formulated to achieve the proposed objective:

- Question 1 : What is the right methodology for fast acquisition, transformation and storage of large amount of parameters (critical parameters) originating from various machines in a complex manufacturing process?
- Question 2 : What is a suitable data integration strategy to support the implementation of the proposed methodology?

3.4 Scope

This work focuses on the creation of a standard and uniform data creation to storage methodology for the machines on the factory floor. It includes the understanding of the interplay between the different machines, stakeholders and the development of information data models to capture and structure the data created in the machines. While the goal is to provide an end-to-end digitalization methodology for complex manufacturing processes, this work does not consider data created by or attached to the product beyond the manufacturing plant such as sales, usage or recycling data. It also does not provide guidance on how to best derive insights from the stored data.

Chapter 4

Proposed Methodology

This chapter provides a comprehensive overview of the methodology utilized for achieving industrial machine connectivity and data acquisition, known as the Methodology for Industrial Digitalization of Complex Processes (MIDCOP).

The proposed methodology (MIDCOP) addresses the conceptual and technical requirements inherent to the digitalization of complex manufacturing processes, effectively bridging the gaps present in existing methodologies as outlined in Table 3.3.

MIDCOP has been developed with the purpose of mitigating persistent challenges encountered in manufacturing data analytics, such as dealing with incomplete, unstructured, incorrect, and unrecorded data. In addition to presenting a robust digitalization strategy encompassing data generation to data storage, MIDCOP also delineates the roles and responsibilities of all stakeholders involved in the digital transformation process.

The genesis of MIDCOP can be traced back to an analysis of the digital transformation undertaken in a battery cell production pilot line. This analysis involved close collaborations with industry experts and digitalization researchers, resulting in an iterative implementation of the key concepts incorporated in MIDCOP.

The culmination of these collaborative efforts, combined with current industry best practices, has yielded a 6-step methodology (Figure 4.1). These steps include: defining critical parameters, assigning labels to machine sensors and actuators, constructing a data model, mapping the data model to machine sensors and actuators, transporting, transforming, and storing data, as well as visualizing and controlling data quality.

The subsequent sections will delve into each step of the methodology in detail, providing a comprehensive understanding of its practical implementation.

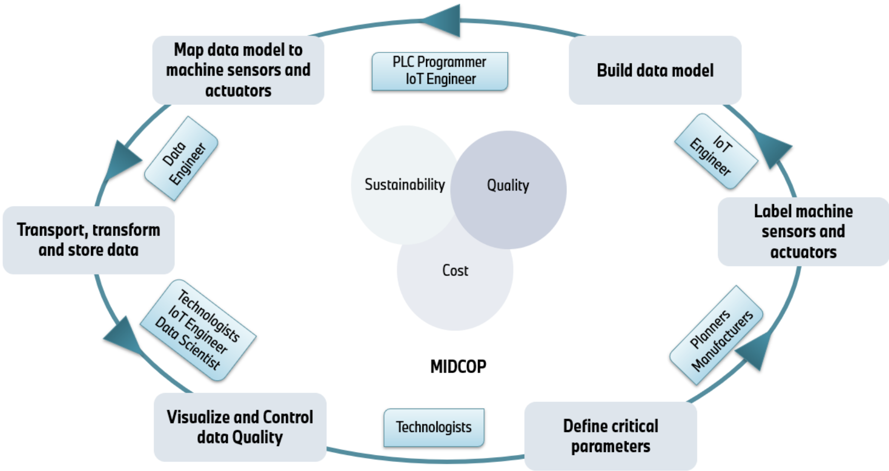

Figure 4.1: Methodology for Industrial Digitalization of Complex Processes (MIDCOP)

4.1 Define critical parameters

The first step of the methodology involves the formulation of the business objectives for the digitalization of the production plant. These business objectives may include enhanced sustainability, superior product quality & lower manufacturing cost; and guide the identification of critical parameters that should be monitored during the production activities. The creation of the list of critical parameters entails the following tasks:

- Enumerate the business objectives of the digital transformation effort e.g., sustainability, quality, traceability, cost.
- Determine the quantity and characteristics of the machines required on the factory floor to manufacture the products and fulfill the business objectives.
- Specify the categories of parameters such as technical measurements, recipe values, machine states and material, product, intermediate process, process IDs necessary to achieve the business objectives.
- Distinguish parameters that will contribute to in-line continuous data, batch data or data aggregated per shift.
- Propose, for each data entry, the suitable engineering unit, frequency of acquisition, a consistent nomenclature and the need for control limits.

The initial step of the methodology involves the formulation of precise business objectives and the subsequent definition of critical parameters. This process ensures a comprehensive data acquisition plan that supports the digitalization efforts and facilitates the attainment of desired outcomes within the manufacturing plant.

4.2 Label machine sensors and actuators

This step implements a structured identification system within the manufacturing plant to ensure unique identification of all its components. Through comprehensive labeling of the entire factory floor, individual components can be monitored, and the traceability of measured critical parameters can be facilitated. The manufacturing plant can be subdivided into six layers: *production line, buildings, machines, segments, processes & sensors, and critical parameters*.

- The production line encompasses the entire factory, from the initial stages of the product to its packaging.
- Buildings refer to the different edifices within the manufacturing facility that house various production elements.
- Machines consist of equipment from different vendors, specifically designed to fulfill specific tasks in the product manufacturing process.
- Segments represent distinct sections of machines, differentiated by their mechanical structure or functionality.
- Processes and sensors identify the origin of critical parameters, with some parameters directly measured by sensors or dedicated devices, while others are generated during or after production processes.
- Critical parameters are measured or calculated values that provide insights into the manufacturing process. In addition to the parameter value itself, they may include engineering units and control limits when necessary.

The figure below illustrates a tree structure that represents the manufacturing plant. While the specific structure of each manufacturing plant may differ based on its unique characteristics, adopting the proposed tree schema enables the consistent and distinctive identification of all relevant components essential for parameter traceability. By implementing this approach, the potential for invalid and untraceable data is minimized, consequently enhancing data reliability and integrity throughout the digitalization process.

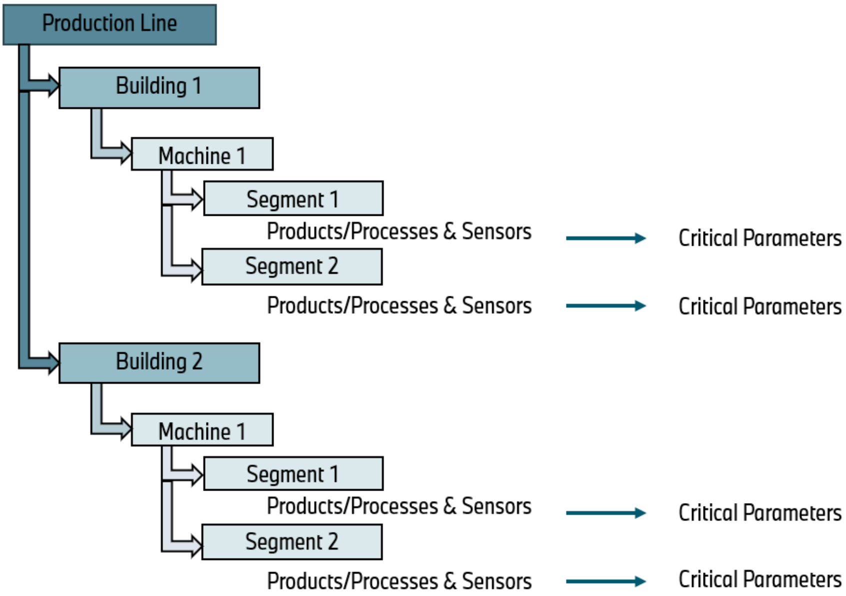

Figure 4.2: Typical tree structure of a factory floor and its machines. Adapted from [30]

4.3 Build custom information model

Building custom information models for all machines on a factory floor is crucial for the digitalization of complex manufacturing processes, especially when utilizing OPC UA as the information exchange standard. These tailored models provide a standardized representation of each machine's data and functionalities, facilitating seamless communication and interoperability. The information model aims to convert the static tree structure of the factory into a living digital twin of the plant. Furthermore, thanks to its object-oriented architecture, the OPC UA information modelling allows for an in-depth contextualization of the measured critical parameters. That is, in addition to the mere measured value, the information model can incorporate a description of the parameters, their suitable datatypes, units, and features of the measuring sensors. Customizing the information model allows precise mapping of machine-specific attributes and parameters, ensuring consistent and meaningful data exchange. It simplifies integration, promotes scalability, and enables real-time monitoring, control, and analysis of critical parameters by

SCADA systems[1].

An accurate information model should showcase *integrity* (include all the different layers of the plant with rich information), *scalability* (facilitate changes over time), *consistency* (provide uniform information descriptions across the plant) and *flexibility* (be capable of integrating diverse features/functions of the machines) [27]. In addition, an accurate information model for a machine on the factory floor requires a combination of domain knowledge, careful analysis of the machine's characteristics, adherence to OPC UA standards, and the effective implementation of the information model within the OPC UA server.

The information models establish a foundation for a robust digital infrastructure, enabling advanced analytics and AI applications, and fostering collaboration across machines, systems, and stakeholders.

4.4 Map information model to machine sensors and actuators

This step proposes the establishment of a connection between the variables generated in a machine's Programmable Logic Controller (PLC) and the custom OPC UA information model.

The PLC serves as an interface between the physical machinery and digital systems, acquiring data from sensors for real-time monitoring and process optimization. Through this digital representation, the PLC enables the digitalization of manufacturing data, making it accessible for further analysis and integration into higher-level systems.

By mapping the PLC variables with the custom OPC UA information models, the data from the PLCs can be effectively represented and interpreted within the OPC UA information space. This mapping ensures proper labeling, organization, and accessibility of the data, facilitating its utilization for analytics. Additionally, it enables a standardized approach to data modeling and communication, simplifying the integration of new machines or technologies from different vendors.

This mapping step involves several tasks, including:

- Verifying the existence of the critical parameters in the PLC as listed in *Step 1 Define critical parameters*
- Creating additional variables in the PLC of the machine as necessary
- Linking each PLC parameter to its corresponding parameter in the custom information model

[1] These systems (Supervisory Control and Data Acquisition) are used to remotely monitor, control, and gather data from industrial processes and infrastructure in real-time.

- Loading the mapped information model on the OPC UA server of the machine

These tasks ensure the accuracy and proper structure of the data flowing through the data pipelines.

4.5 Transport, transform and store data

This work proposes a comprehensive data integration strategy that encompasses three pillars: data acquisition, data transport and transformation, and data storage. These pillars are crucial for establishing a robust and efficient data ecosystem within the manufacturing environment.

Figure 4.3: Data integration strategy

The first pillar, data acquisition, focuses on the collection and capture of data from various machines within the manufacturing system. It ensures a continuous flow of accurate and timely data, forming the foundation for subsequent analysis.

The second pillar, data transport and transformation, addresses the seamless movement of data from its source to the desired destination. This involves employing appropriate communication protocols and technologies to securely transmit the acquired data. Additionally, data transformation processes such as data aggregation and filtering may be applied to ensure the data is in a standardized and usable format. This pillar also involves integrating data from different sources, enabling interoperability and facilitating a holistic view of the manufacturing system.

The third pillar, data storage, focuses on the secure and scalable storage of the acquired and transformed data. This includes establishing databases that can efficiently handle large volumes of data generated by the manufacturing system. Implementing appropriate data storage solutions, such as cloud-based or on-premises databases, enables easy accessibility, retrieval of historical and real-time data for analysis.

Additionally, cybersecurity measures are vital to protect data integrity and confidentiality throughout the entire data pipeline. In terms of cybersecurity proposals, access control and authentication mechanisms, such as multi-factor authentication and role-based access controls, play a crucial role in controlling access to critical data. Data encryption techniques ensure data remains unreadable without proper decryption keys, safeguarding it at rest and in transit. Regular software updates, including security patches, are essential to address vulnerabilities and minimize the risk of exploitation.

The selection of specific commercial technologies to embody these pillars can be tailored to each production plant's unique digital system characteristics and requirements.

4.6 Visualize and control data quality

Upon the implementation of the data integration strategy, it becomes imperative to tackle data quality challenges, as the integrity and precision of data are vital for informed decision-making in complex manufacturing processes. Poor data quality can significantly impact the accuracy of applications that rely heavily on data inputs to perform tasks such as machine learning, predictive maintenance, and real-time monitoring.

Geekiyanage et al. enumerate the main data quality issues in processes such as invalid data, inaccurate data, incomplete data (missing data), inconsistent data and redundant data [31]. These data quality issues are further explained in Figure 4.4. In addition, the researchers highlight several data quality challenges, including time delays, sensor malfunctions, errors in user input, lack of communication, and data corruptions. These challenges are inherent and can emerge irrespective of the magnitude of the manufacturing process.

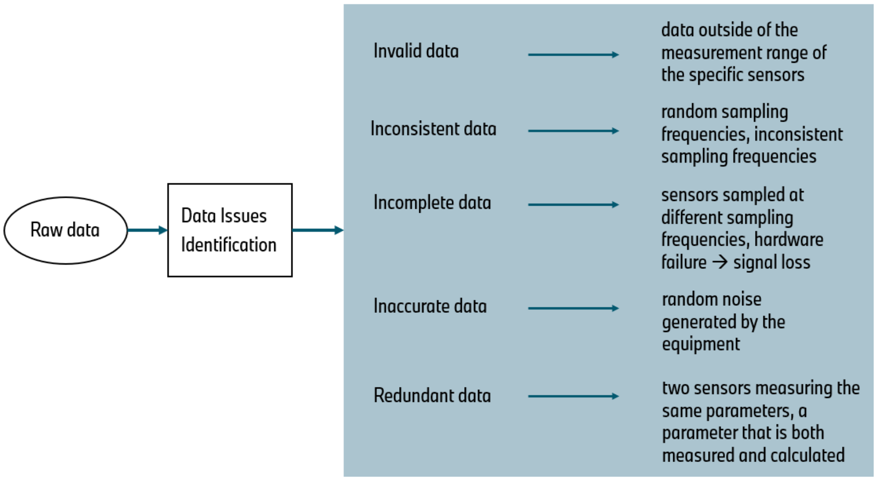

Figure 4.4: Main data quality issues. Adapted from [31]

On the other hand, Pipino et al. [32] investigate data quality metrics to assess the data quality of a given organization. They introduce principles for developing effective data quality metrics, considering both subjective perceptions (of the people involved with the data) and objective measurements (on the dataset). They claim that a universal set of metrics is insufficient, as data quality assessment is an ongoing effort that demands understanding. Nevertheless, they propose key data quality dimensions that should inspire any data quality assessment. These data quality dimensions are reported in Figure 9.3. Moreover, Wilson [33] suggests a data pipeline evaluation approach centered around business value, mechanisms to prevent the proliferation of bad data, maintenance burden of the data pipeline and design patterns to minimize computation and storage costs. The author distinguishes basic, intermediate and advanced data quality checks necessary to assess a data pipeline (Figure 9.4).

Consequently, the key stakeholders involved in the data management -the collectors (IoT), the custodians (data engineers / data steward), and the customers of data (technologists)- need to collaborate in designing a tailored data verification method. This method should address the data quality challenges identified by Geekiyanage et al. [31], and consider the data quality dimensions proposed by Pipino et al. [32] and Wilson [33]. Furthermore, the sequence of steps in the verification method must be adapted to the unique complexities and requirements of the manufacturing process under consideration.

On top of the verification methods, visualization techniques and dashboards can provide a visual interface for data quality checks, helping to identify and address issues, monitor data quality in real-time, and gain valuable insights into data integrity. These tools assist in data validation by visually indicating when data fails validation rules or falls outside of predefined ranges. For instance, histograms, scatter plots, and box plots may provide insights into data quality characteristics, helping end users understand patterns and detect unusual behavior of machines/devices/parameters.

4.7 The stakeholders

For a successful digital transformation of manufacturing processes, organizations should define the responsibilities of the stakeholders and hold them accountable. The SIPOC (Supplier-Input-Process-Output-Customer) diagram[2] can provide a visual representation of the entire digitalization ecosystem (methodology and stakeholders), highlighting the interdependencies and interactions between suppliers, inputs, processes, outputs, and customers. Clarifying the roles and responsibilities fosters effective collaboration, communication, and accountability among stakeholders, ultimately leading to a swift digitalization of the manufacturing processes.

[2]The SIPOC diagram, widely used by Six Sigma practitioners, gained popularity through its association with the Total Quality Management (TQM) movement of the 1980s. This diagram emerged as a valuable tool for identifying stakeholders within an organization and visualizing their interconnected relationships. Its purpose was to provide a comprehensive overview of the key players involved and their interactions with one another.

Chapter 5

Case Study

As described in Chapter 2 *Battery Cell Production and IoT*, the electrode manufacturing process, particularly mixing, is complex and can benefit greatly from digitalization. With numerous variables at play, precise control of factors such as material composition is crucial. Manual monitoring and control can lead to inconsistencies, while digitalization enables real-time monitoring, data analysis, and automated control. Digitalization is, thus, essential in the electrode manufacturing process to achieve consistent quality, streamline operations, and meet industry demands. This thesis proposes to apply MIDCOP to the electrode manufacturing and illustrate its practical implementation.

5.1 Define critical parameters

The business objectives in electrode manufacturing, including gaining deep insights into the process steps, detecting early-stage scrap, and reducing production errors [12], align with the three overarching themes of the proposed methodology: enhanced sustainability, superior product quality, and lower manufacturing costs.

Fulfilling the said objectives requires a comprehensive identification and definition of critical parameters that have a significant impact on the final battery cell quality and production efficiency. By monitoring these parameters in real-time through digitalization, manufacturers can gain insights into the intricate interdependencies and optimize process workflows accordingly.

In their study on battery cell production, Heimes et al [13] present various mixing technologies and tools as effective means to blend active materials & additives, and form the slurry. These technologies include intensive mixers, planetary mixers, dispersers, and extruders. After the mixing, the slurry can then be conveniently packaged in containers and transported to the coating machine.

Based on the requirements outlined in the proposed methodology and the findings from the studies by Kampker et al. [15] and Haghi et al. [12], the following list of critical parameters is suggested to effectively capture the technical requirements of the mixing process and meet the business objectives of the electrode manufacturing.

Parameter name	Unit	Category	Frequency	Datatype
Raw Materials				
Material ID	-	Product	Batch	String
Solid content	%	Product	Batch	Float
Density	kg/m^3	Product	Batch	Float
Purity	% or ppm	Product	Batch	Float
Humidity	%	Product	Batch	Float
Particle shape	-	Product	Batch	String
Step 1: Mixing (dry)				
Slurry formulation	g or wt%	Product	Continuous	Float
Mixer type	-	Equipment	Batch	String
Tank capacity	L	Equipment	Batch	Float
Mixing duration	min	Process	Batch	Float
Mixing temperature	°C	Process	Continuous	Float
Mixing speed	RPM	Process	Continuous	Float
Agglomerate size	µm	Product	Continuous	Float
Step 2: Dispersing (wet)				
Mixer type	-	Equipment	Batch	String
Tank capacity	L	Equipment	Batch	Float
Mixing duration	min	Process	Batch	Float
Mixing temperature	°C	Process	Continuous	Float
Mixing speed	RPM	Process	Continuous	Float
Viscosity	Pa*s	Product	Continuous	Float
Agglomerate size	µm	Product	Continuous	Float
Surface tension	N/m	Product	Continuous	Float
Slurry density	g/cm^3	Product	Continuous	Float
pH value	-	Product	Continuous	Float
Solids content of the slurry	wt%	Product	Continuous	Float
Slurry purity	%	Product	Continuous	Float
Mass Total Slurry	kg	Product	Batch	Float

Table 5.1: List of critical parameters for the mixing. Adapted from [15] & [12]

5.2 Label machine sensors and actuators

In order to complete the mixing step efficiently, this thesis adopts the setup proposed by Heimes et al. [13], which includes a planetary mixer, disperser, intensive mixer, and tank [34]–[36] (Figure 2.2).

The planetary mixer operates by employing stirrer blades that rotate individually on their axes while simultaneously revolving around the mixing vessel. This continuous motion promotes the recombination and movement of batch components within the vessel, resulting in a homogeneous state [34]. The disperser, on the other hand, operates at high speeds and plays a crucial role in mixing solids into liquids, effectively breaking down powdery lumps and ensuring their even distribution in the liquid [35]. Similarly, the intensive mixer utilizes rapidly rotating blades to transfer high energy, breaking bonds and conglomerates between particles and achieving near-complete destruction. Its primary function is to thoroughly mix and evenly distribute additives [36]. Finally, the tank collects the produced slurry over time and is subsequently transported to the coating station once it reaches its capacity.

According to the proposed methodology, the manufacturing plant should be divided into six layers: *production line, buildings, machines, segments, processes & sensors, and critical parameters* to ensure the uniqueness of all the components and full traceability of the critical parameters. The figure below depicts the 6-layer tree structure of the mixing process.

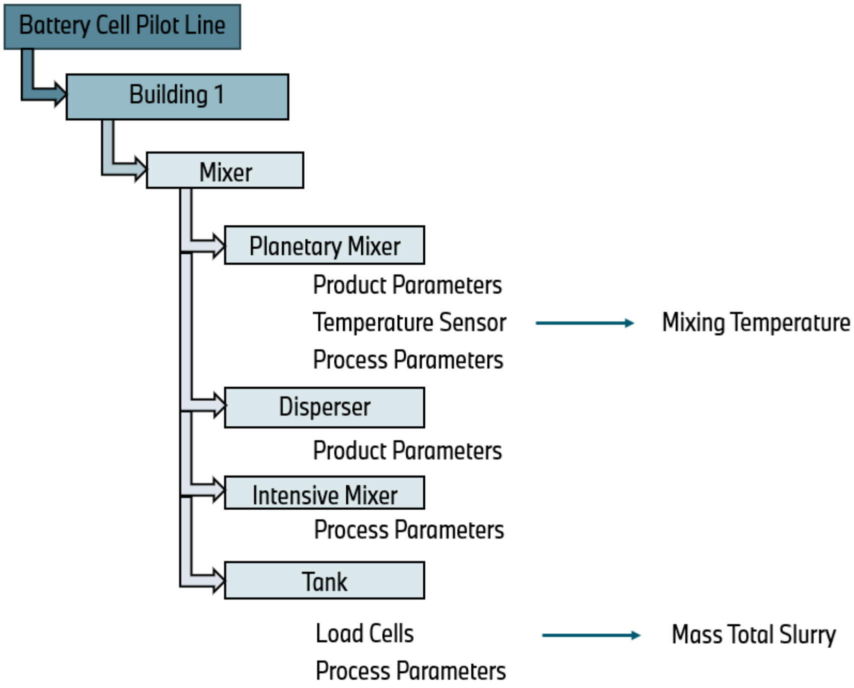

Figure 5.1: 6-layer tree structure of the mixing machine

5.3 Build custom information model

To build a custom OPC UA information model for the mixing machine in battery cell production, several steps need to be followed. Firstly, a thorough understanding of the mixing machine's functionalities, data attributes, and parameters is necessary. This involves analyzing the machine's specifications, documentation, and interactions with other components within the production process. Therefore, *Step 1 Define critical parameters* and *Step 2 Label machine sensors and actuators* of the proposed methodology are prerequisites as they will lead toward achieving such comprehension.

Once the machine's characteristics are understood, the next step is to design the information model structure. This includes defining the data types, variables, and relationships that accurately represent the mixing machine's data and functionalities. It is also crucial to align the information model with the business objectives of the electrode manufacturing process *(gaining deep insights into the process steps, detecting early-stage scrap, and reducing production errors)*.

The information model should incorporate the necessary variables for monitoring and controlling the mixing machine as described in *Step 1 Define critical parameters*. Furthermore, the model has to reflect the physical structure of the machine to indicate the origin of the measured parameters, products and processes. The information model should also adhere to the OPC UA standards and conventions[1]. This involves utilizing OPC UA concepts such as object-oriented modeling, using OPC UA-defined data types, and implementing appropriate data access and security mechanisms.

Figure 5.2 showcases a custom information model for the mixing process with the defined critical parameters attached to the 6-layer tree structure of the pilot line. After designing the information model, it needs to be implemented within the OPC UA server that interfaces with the mixing machine. This involves configuring the server to expose the defined variables, data types, and methods according to the OPC UA specification.

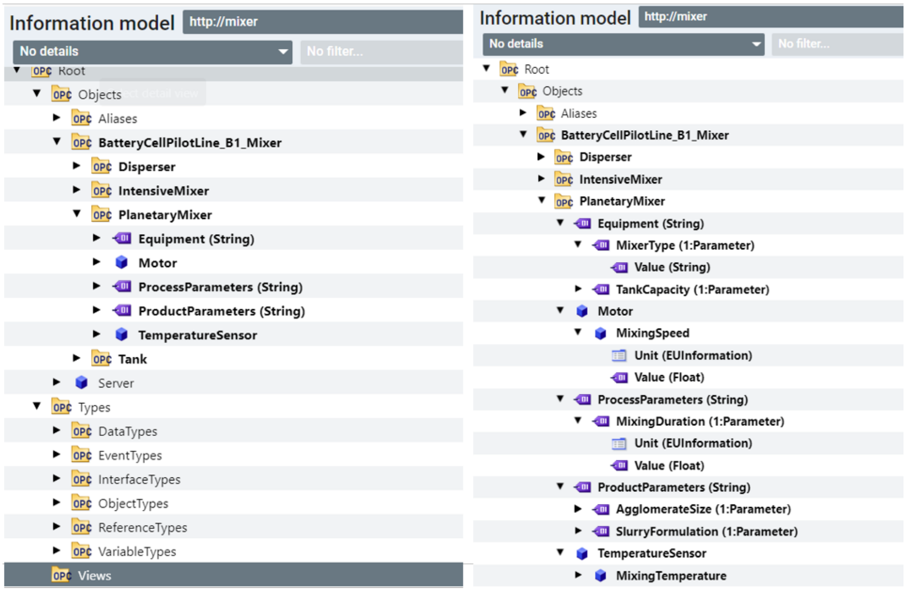

Figure 5.2: OPC UA Information Model of the mixing process

[1]The OPC UA standards and conventions are maintained by the OPC Foundation can be accessed via https://reference.opcfoundation.org/

5.4 Map information model to machine sensors and actuators

In the context of the mixing process of the electrode manufacturing, a mapping is conducted to connect the variables generated in the Programmable Logic Controller (PLC) of the mixing machine with its custom OPC UA information model developed in Figure 5.2. It is worth mentioning that since variable naming in the PLCs of different manufacturers often carry names that are not humanly understandable as shown in Figure 5.3, the said OPC UA information model provides a method to consistently name the variables according to the requirements of the end customer or data analyst.

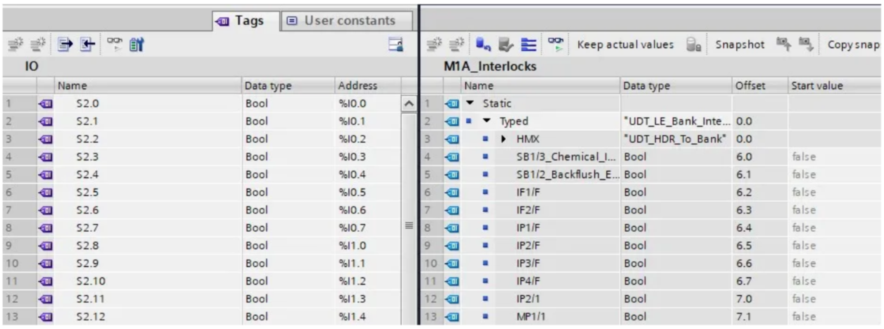

Figure 5.3: Samples of not humanly understandable variable names in PLCs [37]

To establish the mapping, as indicated in *Step 4 Map information model to machine sensors and actuators* of the proposed methodology, the critical parameters required for the mixing process are identified and verified in the PLC. Then, each parameter in the PLC is linked to its corresponding parameter in the custom OPC UA information model. This ensures that the data generated by the mixing machine is accurately represented and contextualized.

Once the mapped information model is loaded on the OPC UA server, the mixing machine's data becomes part of a structured and standardized information space, facilitating seamless data exchange and interoperability.

The following figure shows all the parameters included in the information model mapped with their corresponding PLC variables.

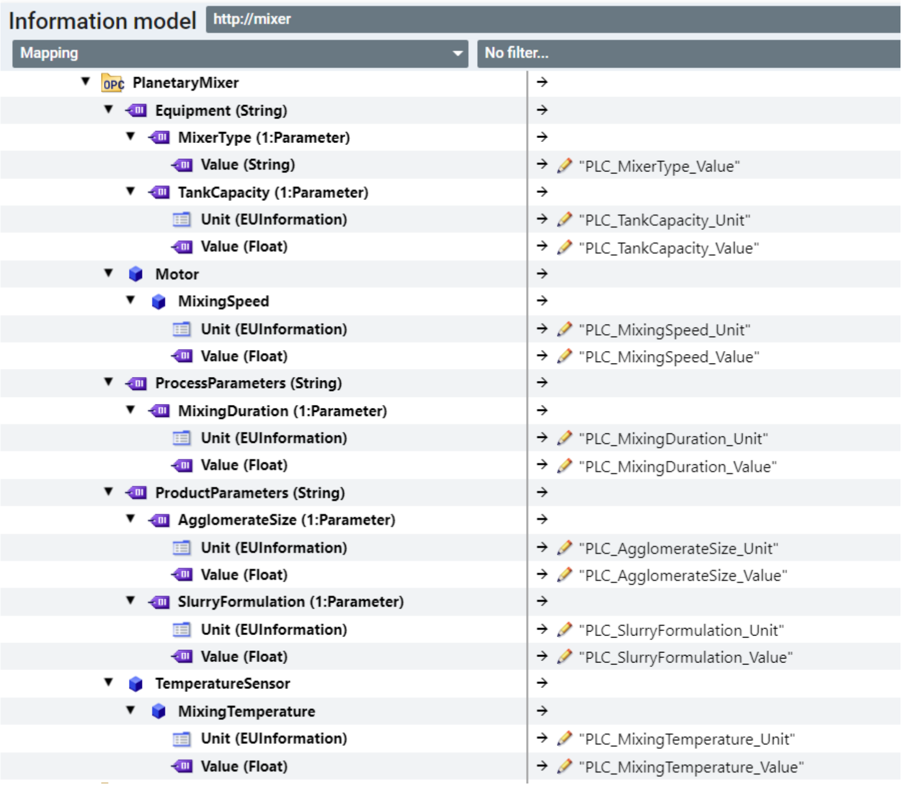

Figure 5.4: Mapped OPC UA Information Model of the mixing process

5.5 Transport, transform and store data

The 3-pillar data integration strategy is applied to the mixing step of the electrode manufacturing process (Figure 5.6).

Regarding data acquisition, the PLC of the mixing machine continuously monitors and updates the values of critical parameters, with each PLC cycle resulting in varying values. The OPC UA server installed on the machine acts as a bridge between the PLC and the data integration process (Figure 5.5). The OPC UA server consistently requests data from the PLC and receives the available values at a high frequency, such as every 50 or 100 milliseconds [38]. Whenever new data is received from the PLC, different from the previous cycle, the OPC UA server publishes these parameters to the OPC UA client, typically at a rate of every 100 milliseconds [38].

Data transport and transformation starts with the OPC UA client that acknowl-

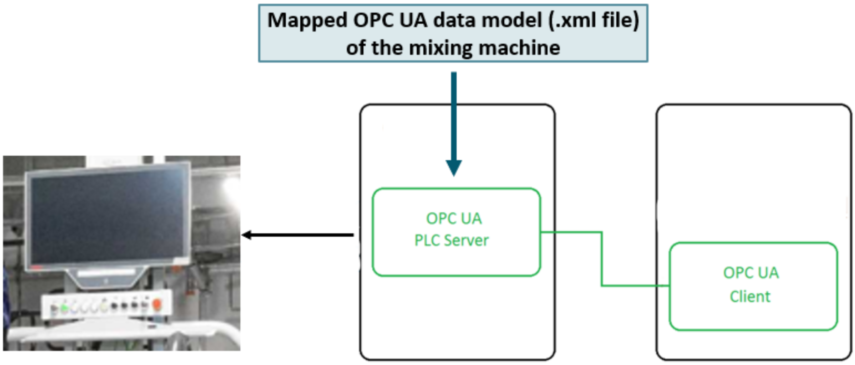

Figure 5.5: Interactions between PLC, OPC UA server and OPC UA client

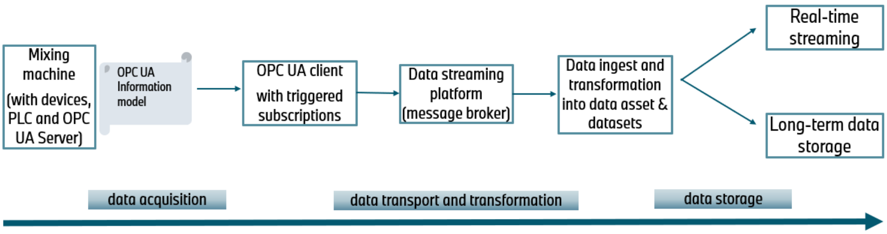

Figure 5.6: Data integration strategy

edges the reception of the data and transmits the parameters to a data streaming platform. This platform serves as a central data hub that allows multiple producers to write data to topics, and multiple consumers to read from these topics according to the publisher/subscriber model[2]. This decoupling of data producers and consumers enables asynchronous communication and ensures that data can be ingested and processed at different rates without impacting the overall system performance. Dedicated consumer programs can then subscribe to the incoming messages to ingest and transform the individual paquets into queryable tabular databases.

The transformed data assets provide a structured format (such as tables) that

[2]Subscribers are clients that express interest in specific data and receive updates when that data changes. Publishers, on the other hand, are servers that provide the data and notify all subscribed clients whenever there is new information available. This model enables efficient and real-time data exchange in industrial systems, allowing subscribers to stay up-to-date with the latest information without continuously polling for updates.

facilitates further analysis and enables the implementation of various data-driven techniques. The choice between long-term data storage and real-time storage depends on specific needs. Long-term data storage is suitable for infrequently accessed or rarely needed data, while real-time data storage is designed for time-sensitive applications (actively generated, processed, and accessed data in real-time or near real-time).

In a nutshell, this step collects the structured parameters from the mixing machine as messages, transforms the payloads into data assets that can be stored on the cloud. Sample payloads and data assets are shown in Figure 5.7 and 5.8 respectively.


```json
{
    "nodeType": "Float",
    "nodeId": "ns=4;s=\"Root\".\"Objects\".\"Mixer\".\"TemperatureSensor\".\"Temperature\"",
    "serverTimestamp": "2023-06-22T13:36:26.6984871Z",
    "sourceTimestamp": "2023-06-22T13:36:26.6984871Z",
    "status": "Good",
    "value": {
      "Value": 19.5,
      "Unit": "°C"
    }
```


Figure 5.7: JSON Payload - Content of one message from the mixing machine

#	ts_utc	message_id	data_key_val_string	measured_value
1	2023-06-15 10:36:33.777787 UTC	cc22074c-ee08-4fd1-986c-c43377b2...	ns=4;s="Root"."Objects"."Machine...	19.83507
2	2023-06-15 07:44:52.873863 UTC	cc22074c-ee08-4fd1-986c-c43377b2...	i=2260	{"ProductUri":"https://www.sieme...
3	2023-06-15 10:23:07.777782 UTC	e81f533c-caec-498b-88dd-b598f4d...	ns=4;s="Root"."Objects"."Machine...	19.89294
4	2023-06-15 07:44:52.873863 UTC	e81f533c-caec-498b-88dd-b598f4d...	i=2260	{"ProductUri":"https://www.sieme...
5	2023-06-15 10:27:10.777784 UTC	d257c65f-b538-46fe-8cf8-b5586c9d...	ns=4;s="Root"."Objects"."Machine...	19.89294
6	2023-06-15 07:44:52.873863 UTC	d257c65f-b538-46fe-8cf8-b5586c9d...	i=2260	{"ProductUri":"https://www.sieme...
7	2023-06-15 10:07:34.277786 UTC	57ba68e4-9601-4f0c-86a1-a9585c3...	ns=4;s="Root"."Objects"."Machine...	19.83507
8	2023-06-15 07:44:52.873863 UTC	fa2dd5ef-89ad-4452-9810-13fd0427...	i=2260	{"ProductUri":"https://www.sieme...
9	2023-06-15 10:23:36.777786 UTC	2fb68976-fac2-46da-ae12-e4d9388...	ns=4;s="Root"."Objects"."Machine...	19.878473
10	2023-06-15 07:44:52.873863 UTC	2fb68976-fac2-46da-ae12-e4d9388...	i=2260	{"ProductUri":"https://www.sieme...
11	2023-06-15 10:30:47.277785 UTC	824f3f5f-789e-49ed-a671-631b14fc...	ns=4;s="Root"."Objects"."Machine...	19.849537
12	2023-06-15 07:44:52.873863 UTC	824f3f5f-789e-49ed-a671-631b14fc...	i=2260	{"ProductUri":"https://www.sieme...
13	2023-06-15 07:44:52.873863 UTC	57ba68e4-9601-4f0c-86a1-a9585c3...	i=2260	{"ProductUri":"https://www.sieme...
14	2023-06-15 10:47:13.777788 UTC	f5a8dfcd-f2c6-4892-a2f2-79b6fc59c...	ns=4;s="Root"."Objects"."Machine...	19.849537

Figure 5.8: Data asset with structured data from messages

As far as the application of data-driven methods such as data mining, data analytics and AI is concerned, this data transformation step is of great importance as raw data created in the mixing machine can not be stored as is in the cloud nor on premise databases.

5.6 Visualize and control data quality

The successful implementation of the preceding five steps in the MIDCOP methodology culminates in the creation of a demonstration dashboard (Figure 5.9). This dashboard exhibits real-time temperature data acquired from a sensor in the planetary mixer during the period between 18th June 2023 and 19th June 2023, with a sampling and publishing frequency of approximately 100 milliseconds.

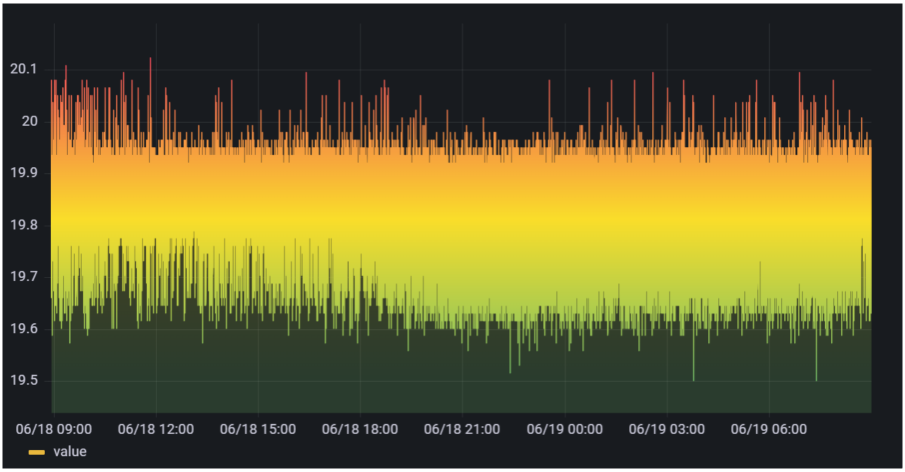

Figure 5.9: Dashboard with temperature data from the planetary mixer

After the visualization dashboard is developed, the subsequent step involves conducting a data quality check. To achieve a comprehensive data quality checklist tailored to the mixing process, the common data quality issues and dimensions outlined in the proposed methodology must be considered. During the production campaigns of the mixing machine, the implementation of the following checklist becomes imperative to ensure data integrity and reliability:

1. Collect data over a sufficient number of batches of materials (at least 3 or 4) to ensure representativity of the data
2. Verify the functionality of all sensors in the machine, ensuring they provide valid and accurate data
3. Compare the data displayed on the machine's Human Machine Interface (HMI) with the data transmitted via the OPC UA client to identify any discrepancies
4. Validate the uniqueness of all data entries to prevent duplicate or conflicting information

5. Confirm that the OPC UA client transmits all types of data structures accurately without any loss or corruption
6. Validate the correct data structure on the data streaming platform and ensure consistency with the data asset
7. Utilize additional dashboards and visualization tools to visually inspect data patterns, identifying any anomalies or outliers

5.7 The stakeholders

In the digitalization of the mixing process, various stakeholders play crucial roles, as indicated in the proposed methodology and depicted in the SIPOC diagram (Figure 5.10):

- Technologists are responsible for identifying and defining the critical parameters that need to be monitored and controlled during the mixing process. They establish the specifications and requirements for data collection and analysis.
- Manufacturers label each component included in their machines. This labeling ensures that the components can be accurately identified and integrated into the overall digital system. It facilitates seamless data flow and interoperability.
- IoT engineers build the OPC UA information model, which serves as a standardized framework for contextualizing the parameters measured in the machine. This model provides a structured representation of the data and enables seamless communication between the physical and digital systems.
- PLC programmers map the PLC variables to the information model created by the IoT engineers. This mapping establishes the necessary links between the physical machine and the digital system, enabling real-time data acquisition and synchronization.
- Data engineers oversee the ingest of the individual messages generated by the mixing process from the data streaming platform. They transform these messages into data assets that can be stored, managed, and analyzed effectively. This includes tasks such as data cleansing, integration, and data quality assurance.
- Data scientists leverage the data assets created by the data engineers to apply advanced analytics techniques and algorithms to extract insights and generate meaningful dashboards and reports. These visualizations provide

the technologists with valuable information on the attainment of business objectives related to the mixing process, facilitating data-driven decision-making and process optimization.

Organizations can ensure effective collaboration, accountability, and seamless integration of both the physical and digital aspects of the mixing process in battery cell manufacturing by clearly defining the responsibilities of each stakeholder involved in the digitalization process.

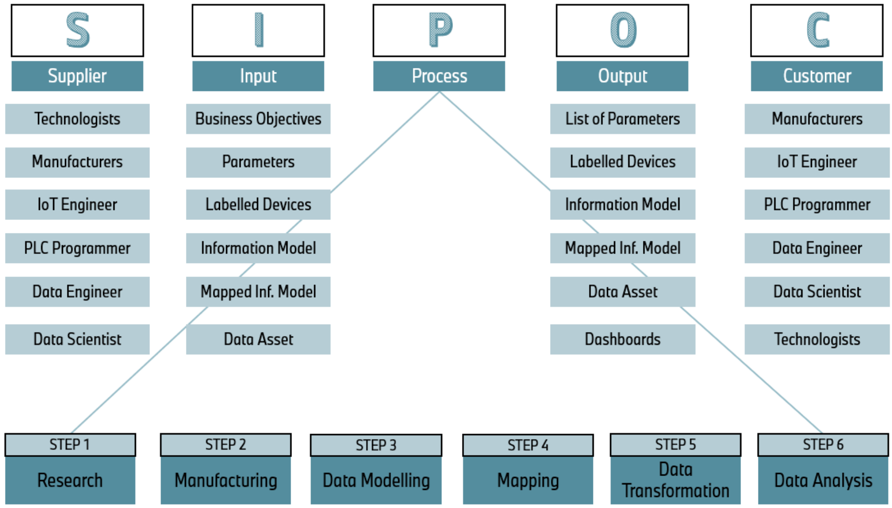

Figure 5.10: SIPOC diagram for the digitalization of complex processes

Chapter 6

Discussions

Complex manufacturing processes such as battery cell production typically incorporate a variety of machines from different manufacturers. The interactions between these machines generate a large amount of measured parameters, intermediate processes and processes. As many battery cell manufacturers start placing sustainability, cell quality and production costs at the center of their priority, data-driven solutions such as data analytics and AI prove to be major enablers of the industrial shift. However, these digital solutions rely on available and accurate data to draw meaningful insights. The lack of standard methodologies to acquire and store data from complex manufacturing processes motivates the two research questions identified at the beginning of this work.

6.1 Research questions

Research Question 1

To allow for the interoperability of the machines on the factory floor, the Methodology for Industrial Digitalization of COmplex Processes (MIDCOP) was proposed. It encompasses six sequential steps that were applied to the mixing process of the battery cell production. These steps further cover the derived conceptual and technical criteria for a successful digitalization of complex manufacturing processes.

The first and second steps of the proposed methodology identify the business objectives set for the digitalization of battery cell production, formulate a list of critical parameters that capture these objectives and call for the manufacturing of customized machines that can perform mixing tasks and provide traceability for the critical parameters. By tracking all the relevant parameters, these steps contribute to enhance sustainable production and set the tone for a comprehensive digitalization of the production process.

The third and fourth steps of the methodology create the connection between the physical (mixing machine) and the digital system (data pipelines). By using protocols independent of vendors such as OPC UA, the methodology guarantees interoperability and connectivity of the different machines. The methodology also provides a workflow to create custom information models that accurately represent the machines, incorporate the critical parameters, and are flexible enough in their structure to allow for scalability. Additionally, the implementation of steps one to four of the methodology ensures a complete automation of the data acquisition phase.

The case study of the battery cell production has proven that by sequentially defining critical parameters, labelling all sensors and actuators in the mixing/coating machines, building tailored OPC UA information model and mapping the PLC variables to the information model, large amount of parameters originating from various machines could be effectively acquired, structured and connected.

Research Question 2

The proposed data integration strategy stands on three pillars: data acquisition (machine sensors, mapped information model, OPC UA server), data transport and transformation (subscriptions from OPC client, data streaming platform, message ingest and data transformation by consumer programs) and data storage (cloud services or on-premise databases). This strategy enables the end-to-end digitalization of the manufacturing processes (data acquisition to storage), facilitates the processing and storage of high-frequency data while accounting for cybersecurity layers needed to safeguard the integrity of the data flowing in the pipelines. The last step of the methodology introduces the concept of data quality checks with the help of visualization tools to assess the validity of the data created by the machines and stored in the databases.

This data integration strategy gives room to the application of the best practices along the entire data pipeline. It also comes with extensive flexibility to adopt novel technological solutions that fit the given use case. Possibility to track the critical parameters from creation to storage, robust cybersecurity, comprehensive quality check are also key features embedded in the strategy.

On the other hand, as the strategy relies on the interplay between different technologies to acquire, transform and store data, integration issues between the different platforms are likely to arise and should be dealt with by skilled practitioners. To successfully implement the strategy, there should be close cooperations with external teams and partners as illustrated in the SIPOC diagram of the mixing process. While the proposed methodology will fill in the gaps left by existing methodologies, it requires extensive design and data engineering work to connect the whole data pipeline.

6.2 Best practices

Successful implementation of the proposed methodology for digitalizing complex manufacturing processes requires adherence to best industrial practices. Key considerations include defining clear objectives aligned with business goals and engaging stakeholders such as control planners, machine manufacturers, technologists, and IoT engineers to incorporate diverse perspectives. Additionally, selecting scalable, secure, and compatible IoT technologies that enable real-time data collection and integration with existing systems is crucial.

To ensure effective data management and protection, organizations should develop a comprehensive plan encompassing data storage, analysis, and security measures. Prioritizing data privacy and security through robust measures like encryption safeguards against cyber threats and breaches. Gradual scaling, starting with a small-scale implementation, allows for thorough testing, validation, and optimization before full-scale deployment.

Continuous monitoring and evaluation of IoT implementation enable issue identification and improvement opportunities. Regular assessment and refinement optimize outcomes. By following these best practices, organizations enhance their chances of successful implementation and harness the transformative potential of digitalization in complex manufacturing processes.

6.3 Socio-economic and environmental aspects

Digitalization has the potential to facilitate sustainable battery cell production across all three dimensions: social, economic and environmental.

6.3.1 Socio-economic aspects

The digitalization of battery cell production for electric vehicles has significant socio-economic implications. Firstly, digitalization enables increased efficiency and productivity in the manufacturing process. By integrating advanced technologies such as robotics, automation, and data analytics, production processes can be streamlined and optimized, leading to higher output and cost savings [39]. This, in turn, can contribute to the affordability and accessibility of electric vehicles, making them more economically viable for consumers.

Secondly, digitalization facilitates improved quality control and product customization. Through real-time monitoring and data analysis, manufacturers can detect and address potential defects or issues in battery cell production, ensuring higher quality and reliability of the batteries. Digitalization also allows for the customization of battery characteristics and configurations, meeting the diverse needs of electric vehicle manufacturers and end-users. This flexibility enhances consumer satisfaction and supports the growth of the electric vehicle market.

Furthermore, the digitalization of battery cell production creates new job opportunities and promotes economic growth. The adoption of digital technologies requires a skilled workforce in areas such as data analytics, robotics, and automation *(IT-specialists, electrochemists, engineers, mechanical experts)* [40]. Consequently, this leads to job creation and the development of expertise in emerging fields.

By 2030, the World Economic Forum (WEF) anticipates the creation of a substantial number of jobs in the global battery value chain, reaching a total of 10 million positions. This will include approximately 90 to 180 direct jobs in battery production per gigawatt-hour (GWh), along with 350 to 1,400 indirect jobs spanning the entire battery value chain [40], [41]. The primary areas for job growth will be in cell manufacturing, battery production, raw material processing, and the recycling of secondary raw materials. However, industry experts have expressed concerns about a potential shortage of skilled workers, with estimates suggesting a shortfall of approximately 800,000 individuals with the necessary expertise across the battery production chain by 2025 [40], [41].

6.3.2 Environmental aspects

Digitalization promotes sustainability and environmental stewardship. By optimizing production processes, reducing waste, and optimizing resource utilization, digitalization helps minimize the environmental footprint of battery cell production. It enables more precise energy management, leading to reduced energy consumption and greenhouse gas emissions. This aligns with global sustainability goals and contributes to a cleaner and greener transportation sector.

Furthermore, digitalization can help address sustainability aspects within battery production. One example is the promotion of transparency throughout the value chain in an effort to prevent future social injustices [39]. The digital twin of the battery cell facilitates this transparency by providing information on production types and material origins. Moreover, it serves as a foundation for automating life cycle assessments (LCA) and supports initiatives such as the Battery Passport. [39]

Chapter 7

Conclusions

This thesis has highlighted the need for digitalization in battery cell production considered as a complex manufacturing process. By embracing end-to-end digitalization, cell producers can effectively achieve their sustainability and quality goals, while also ensuring compliance with the new EU battery regulations. However, the path to digitalization is not without its challenges. These challenges stem from the inherent properties of manufacturing processes and the absence of a comprehensive methodology that covers data acquisition to data storage.

The contribution of this work lies in the development of the Methodology for Industrial Digitalization of Complex Processes (MIDCOP). Consisting of six steps, MIDCOP incorporates all the conceptual and technical criteria derived for a successful digital transformation of complex processes. Moreover, this thesis goes beyond the methodology itself and identifies the specific responsibilities of all stakeholders within the battery production ecosystem through a SIPOC (Suppliers, Inputs, Process, Outputs, Customers) diagram.

The case study, focusing on electrode manufacturing, serves as a concrete demonstration of the effectiveness of MIDCOP in enabling the end-to-end digitalization of complex manufacturing processes.

This thesis advances the digitalization of battery cell production by providing practical insights to industry leaders and researchers, paving the way for future research and implementation efforts in this critical industry.

Chapter 8

Future Work

In addition to the findings presented in this thesis, there are several avenues for future research and implementation in the field of digitalization of complex manufacturing processes.

Further investigations could be conducted to adapt and implement the MIDCOP methodology across all the machines and processes on the factory floor beyond the mixing process. By doing so, a digital twin of the entire battery production system can be realized and will serve as a powerful tool for simulations, predictive control, and optimization.

Furthermore, there is a need to develop tailored methods that leverage the vast amount of data stored in the databases resulting from the implementation of MIDCOP. These methods should aim to harness the data effectively and create, for instance, the digital passport mandated by the EU battery regulation requirements.

It could also be worth exploring methods and strategies to reduce costs related to data ingest and storage as the volume of data in complex systems can be substantial. Techniques such as data compression, data deduplication, or efficient data lifecycle management practices, where less critical data is archived or purged over time, can further contribute to cost savings in the digitalization of complex systems.

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Chapter 9

Appendices

Figure 9.1: BMW Cell Manufacturing Competence Center in Parsdorf (15 000 m^2)[42]

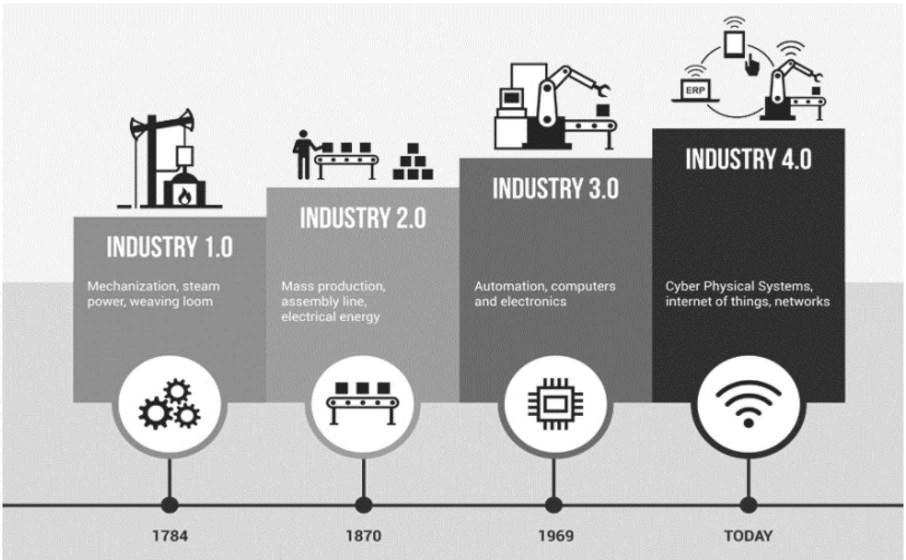

Figure 9.2: The evolution of industry 1.0 to 4.0 [20]

Dimensions	Definitions
Accessibility	the extent to which data is available, or easily and quickly retrievable
Appropriate Amount of Data	the extent to which the volume of data is appropriate for the task at hand
Believability	the extent to which data is regarded as true and credible
Completeness	the extent to which data is not missing and is of sufficient breadth and depth for the task at hand
Concise Representation	the extent to which data is compactly represented
Consistent Representation	the extent to which data is presented in the same format
Ease of Manipulation	the extent to which data is easy to manipulate and apply to different tasks
Free-of-Error	the extent to which data is correct and reliable
Interpretability	the extent to which data is in appropriate languages, symbols, and units, and the definitions are clear
Objectivity	the extent to which data is unbiased, unprejudiced, and impartial
Relevancy	the extent to which data is applicable and helpful for the task at hand
Reputation	the extent to which data is highly regarded in terms of its source or content
Security	the extent to which access to data is restricted appropriately to maintain its security
Timeliness	the extent to which the data is sufficiently up-to-date for the task at hand
Understandability	the extent to which data is easily comprehended
Value-Added	the extent to which data is beneficial and provides advantages from its use

Figure 9.3: Data quality dimensions [32]

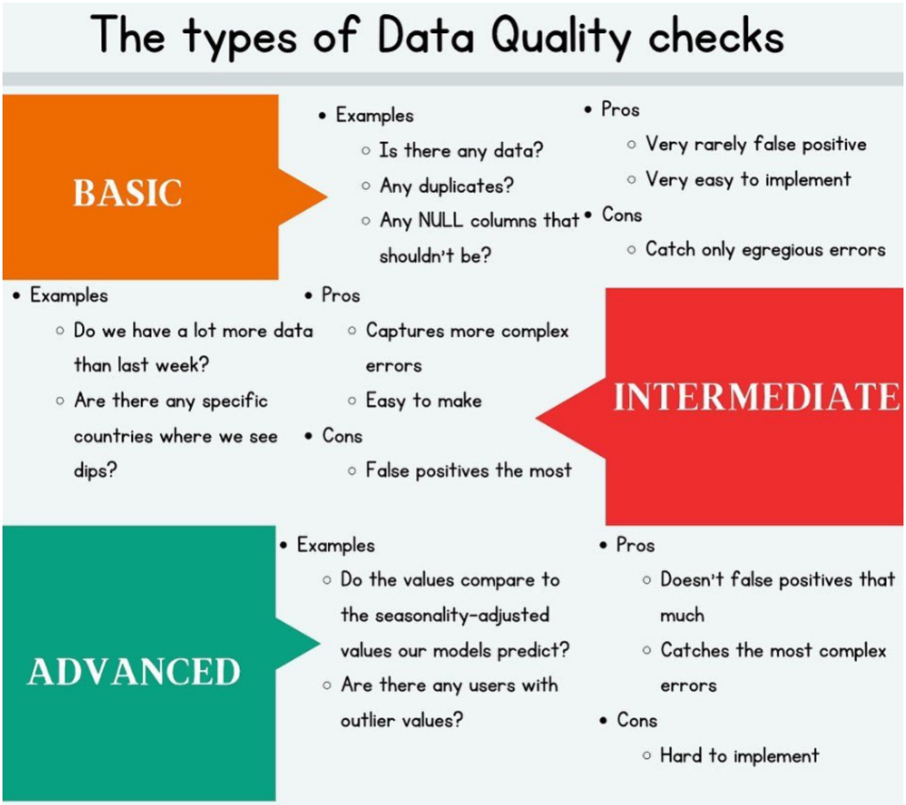

Figure 9.4: Quality evaluation of a data pipeline [33]