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From Machinery to Insights: A Comprehensive Data Acquisition Approach for Battery Cell Production

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Abstract

To ensure the widespread use of sustainably produced battery cells, further progress in research is needed. The transition to automated data acquisition is complicated by the technical complexity of industrial data acquisition. Existing software solutions also fall short in meeting usability, reproducibility, extensibility, and cost-effectiveness requirements for research-scale battery production lines. To address these gaps, this paper presents and evaluates a comprehensive data acquisition and collection solution for research-scale battery production lines. It offers a systematic overview of the industrial data acquisition process, focusing on gathering data from various existing machinery and utilizing the industry standard OPC UA protocol. Given the lack of existing solutions that meet the specified requirements, the paper introduces the "ProductionPilot" software as a solution. “ProductionPilot” is designed to provide an extensible platform with a user-friendly web interface. It enables users to select, structure, monitor, and export live production data delivered via OPC UA. The effectiveness of the proposed system is validated at the CELLFAB battery production research facility at eLab of RWTH Aachen university, demonstrating its capability for long-term data acquisition and the generation of digital shadows. By addressing the limitations of current data collection methods and providing a comprehensive solution, this research aims to facilitate the broader adoption of lithium-ion batteries in renewable energy applications.

Keywords

Battery Cell Production; Industry 4.0; Automated data acquisition; Digitalization; OPC UA

1. Introduction

Batteries play a crucial role in powering our technologically advanced and sustainable future, from electric vehicles to renewable energy storage. To meet the increasing global demand, optimizing battery production processes is essential. Data-driven research has proven pivotal in driving progress across industries, including batteries. By leveraging data analytics, researchers gain valuable insights into battery production, leading to enhanced processes and performance.

Central to data-driven battery research is the development of efficient data gathering and monitoring systems. These systems provide real-time data from machinery and processes, enabling researchers to optimize production lines and embrace automation. This paper presents a comprehensive guideline for digitalizing battery production lines, using the PEM of RWTH Aachen University research production line as a case study. By showcasing the importance of data-driven research and sophisticated data acquisition systems, we aim to enable battery manufacturers and researchers to successfully implement digital transformation of their machine and plant technology.

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2. Research Background

The following sections will delve into digitalization in production, the lithium-ion battery production process, and a comprehensive overview of related work in the field.

2.1 Digitalization in production

The term digitalization describes "the comprehensive networking of all areas of the economy and society as well as the ability to collect, analyse and convert relevant information into actions". [1] When referring to digitalization in production, the term usually refers to data collection by a physical system or process, often designed for a specific purpose. A definition of a digital shadow states that "a digital shadow is a set of temporal data traces and/or their aggregation and abstraction, collected in relation to a system for a specific purpose in relation to the original system." [2] The creation of a digital shadow in battery production research requires the acquisition of data from industrial machines. Industrial connectivity, which involves communication and data exchange between devices in industrial environments, plays a critical role in this process, such as programmable logic controllers, which are the main source of industrial data. It also entails communication protocols such as OPC UA, which is widely used to simplify data collection in industrial applications. [3,4]

Programmable logic controllers (PLCs) are widely used as proprietary technology in industrial machinery for software-based control. They connect to various sensors and actuators, enabling complex machine operations. To enable communication between PLCs, sensors, actuators, computer networks, and other peripherals, a diverse range of interfaces have been adopted within the industry by PLC manufacturers. Common protocols include Profibus, Profinet, Modbus, EtherCAT, and EtherNet/IP. Ensuring data collection from heterogeneous industrial devices can be difficult due to this variety of interfaces. However, the adoption of OPC UA as a common standard for industrial connectivity is gaining momentum, simplifying data acquisition in the industrial sector. [5]

The OPC UA protocol is an industry-standard platform-independent standard that facilitates data transfer between industrial devices and applications. It follows a client-server architecture and uses a binary protocol over TCP/IP for communication. OPC UA allows access to machine variables (tags) through server discovery, enabling reading, writing, and subscription-based monitoring. Subscribed clients receive updates when changes occur, with customizable sampling rates for data collection. OPC UA also offers encryption, event handling, and remote method calling. Despite its complexity, OPC UA is widely adopted and serves as a powerful tool for accessing and monitoring data in industrial applications. [5,6]

2.2 Lithium-ion battery production process

The process chain of lithium-ion battery cell production includes several essential steps. The main sections are electrode manufacturing, cell assembly and cell finishing (see Figure 1). The electrode manufacturing starts with the preparation of active materials, i.e., mixing and coating of cathode and anode materials onto metal foils. The active materials are then dried and calendered before the electrode webs are cut into coils. During cell assembly, the next step typically entails winding or stacking the anode and cathode together with the separator to form the cell's core compound. The separator is integrated between the electrodes to prevent electrical short-circuits. Tabs are then welded on, which form the subsequent poles of the battery before the cell is filled with electrolyte. The cell gets hermetically sealed to prevent leakage. In cell finishing soaking and formation processes are conducted to achieve the desired electrochemical cell performance. Lastly, the cell undergoes comprehensive testing and quality checks during aging and EOL testing, ensuring compliance with automotive standards for use in electric vehicles. [7]

In the lithium-ion battery production process, data collection plays a crucial role. Generating vast quantities of data enables to effectively monitor and control the production process to meet the product specifications.

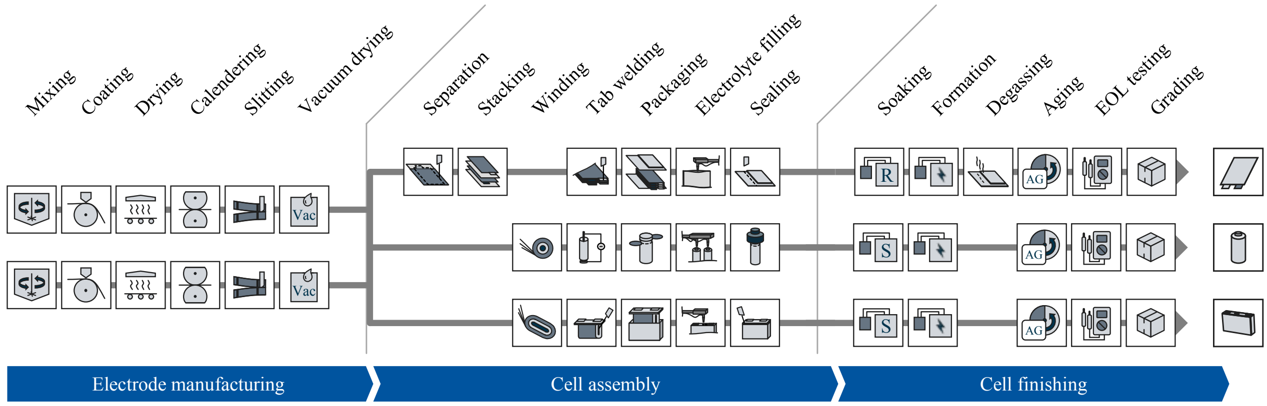

Figure 1: Generic process chain in battery cell production for pouch, prismatic and cylindrical cells [8]

The data is acquired from various sources, e.g., process equipment and programmable logic controllers (PLC), sensors and measuring devices, laboratory and operational records. The acquired data comes in different formats, including time series, databases, tabular data and discrete data files. [9] Discrete data input may contain for instance material property information, data sheets of components as well as equipment features and specifications. [10] In production, a large number of heterogeneous data types are commonly found in the form of structured, semi-structured and unstructured data, including measured values, product records, text, logs, audio, video. [11] The primary objective is to determine the relevant data for the relationship between the process, the intermediates, and the final product. In order to capture this data, a variety of different production machines and analytical devices from diverse suppliers must be accessed. [12]

As different equipment manufacturers are involved in various production steps, there is no uniform framework for seamless data exchange. [13] This hinders efficient data collection and analysis, impacting process optimization. Proprietary data interfaces used by specialized equipment suppliers lead to data silos and compatibility issues. Implementing standardized data interfaces will enable the battery industry to fully leverage data-driven manufacturing, ensuring a successful and sustainable battery production.

2.3 Related Work

Different approaches for the digitalization and data acquisition in battery cell production can be found in the literature. *Ayerbe et al.* generally explore the current status and near-term developments in digitalizing the battery cell manufacturing chain, combining modelling approaches, data acquisition, and communication protocols. [14] In this context, a practical implementation of most approaches has only been realized in research and pilot lines. *Turetskyy et al.* propose a data-driven approach to holistically capture and evaluate interactions between production steps and cell properties in battery cell production. This approach presents a concept for acquiring relevant data throughout the production line, including technical building services and cell diagnostics. The approach combines automated and manual data collection, integrating data from different sources, protocols, and formats for accessible, efficient data management, and visualization. [12] *Han et al.* addressed the challenge of integrating heterogeneous automation equipment in lithium-ion battery manufacturing by establishing a standardized information model. The model allows interconnection and interoperability of data at various network levels, enabling manufacturing informatization and intelligence. The approach maps the information model to OPC UA for data storage and interaction. [15] *Liu et al.* investigate the smart manufacturing of lithium-ion batteries using an event data model for data sharing and interoperability by implementing various sensor nodes and subsystems. Therefore, different components or services in battery cell production can be flexibly integrated and included. [16] *Wessel et al.* introduce a methodology for an ontology-based traceability system in battery cell production. This system integrates various data types and sources, enabling precise tracing throughout the manufacturing process and data organization that can be adapted for similar manufacturing setups in the future. [17] *Zhou et al.* highlight the benefits of a software system based on micro-service architecture for battery cell production by using a supplementary extension scheme to enhance the existing Manufacturing Execution System (MES) without modifying it. The microservice-based approach allows for scalable and agile development, catering to personalized requirements of manufacturing enterprises. [18]

While data acquisition for battery production (at research scale) has been broadly addressed, there is no comprehensive solution for data collection with an industrial data acquisition process integrating a vast variety of machinery and devices yet. Therefore, a solution shall be developed that meets these requirements and provides an extensible platform with a user-friendly web interface to select, structure, monitor and export live production data delivered via OPC UA.

3. Approach

This paper presents a standardized framework for the structured development of a data acquisition and provision system. That encompasses capturing the current state of industrial systems, defining the target state, developing a coherent system design, and implementing the customized solution (see Figure 2). This adapted approach for tailored digitalization concepts [19] aims to optimize industrial data collection, fostering improved performance, user-friendliness and overall system optimization in research-scale battery cell production.

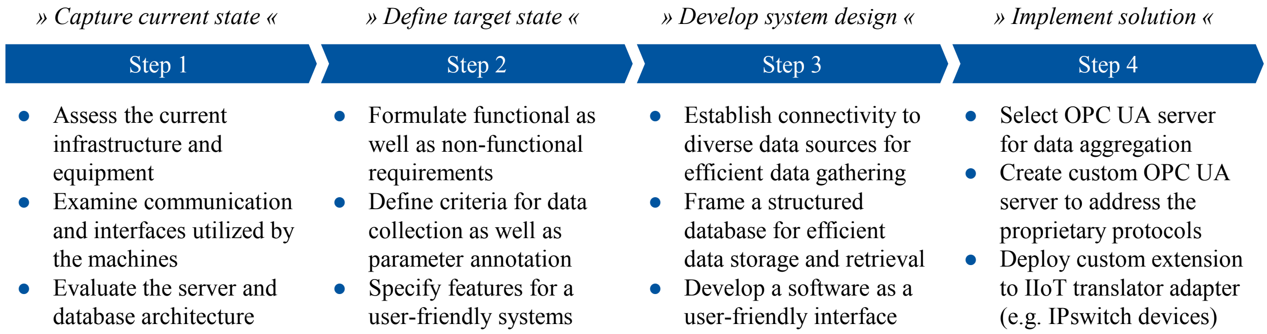

Figure 2: Approach for deriving an automated solution for data acquisition in research-scale battery production

The first step entails an in-depth evaluation of the existing infrastructure, equipment, and machinery. Through a systematic assessment of communication protocols and interfaces, insights into the setup of the current system are gained. The subsequent phase aims to formulate functional and non-functional requirements. These requirements serve as a blueprint for the planned data acquisition and provision system. For this purpose, criteria for data acquisition and parameter annotation are defined to ensure the reliability and integrity of the data. Further emphasis is placed on defining features that will improve usability and simplify the operation of the system. The next step centres on the setup of efficient mechanisms for data acquisition, storage and provision. For this purpose, a corresponding concept is developed based on the requirements from step 2. This includes a database, an OPC UA server, and a data management system. The latter represents the interface between the user and the database as well as the OPC UA server. The final step is the implementation of the concepts from step 3 in a concrete facility. This includes establishing a connection to various data sources to ensure a continuous flow of real-time information as well as selection of a suitable OPC UA server. To overcome proprietary limitations, the OPC UA server will be customized to act as a bridge between legacy systems and new devices. In addition, a custom extension of the "IIoTranslator" adapter is deployed to further improve data communication and translation between industrial components. A structured database is set up that can handle the expected volume of data and enable fast and reliable data retrieval. A user-friendly software interface is developed that facilitates intuitive interactions and system control.

4. Results

Chapter 4 delves into the current state, target state, system design, and implementation of the data collection system for lab-scale battery production research. It elaborates the infrastructure, machines, interfaces, and protocols of the CELLFAB research production line, outlines functional and non-functional requirements, and introduces the components that make up the system, including the OPC UA server, database, and the user-friendly data management system known as Production Pilot.

4.1 Actual state (Infrastructure, Machines, Interfaces, Protocols)

The CELLFAB is a research production line for the manufacturing of lithium-ion battery cells and belongs to the PEM of the RWTH Aachen University. The line is semi-automated and is used for research of production processes as well as new manufacturing technologies. A picture of the CELLFAB in which pouch cells are produced can be found in the Appendix in Figure 6. Especially in the field of laboratory lines for the production of lithium-ion battery cells, there are hardly any turnkey suppliers that cover the entire process chain from end to end. The PEM line, for example, consists of over 20 systems from more than 14 equipment suppliers. In addition, there is a variety of measurement technology and offline equipment from even more suppliers, such as a line scan camera from Isra Vision. The machines are usually connected via their PLC. The fact that the equipment is very heterogeneous is shown, among other things, by the fact that not every system has a PLC and even if it does, these are from different manufacturers or generations. For example, the Bürkle Coater has both a Siemens S7 and an S7-300. The camera integrated into the line (Isra Vision), for example, uses a measuring computer and no PLC at all. To enable the acquisition and analysis of production data, a corresponding IT infrastructure was set up at CELLFAB, which consists of a network including Ethernet cables, switches, gateways and a server on the hardware side. In addition, hardware adapters were used for the connection of equipment that does not have an Ethernet interface. An example of this is the Eirich mixer, which only has a Profibus connection. A Helmholz NETLink PRO was used to integrate this into the system. This adapter provides an Ethernet interface and thus enables communication via Internet protocol. The server represents the central unit of the system in which the data is aggregated and made available. For this purpose, all production equipment was connected to the server via Ethernet cable. On the equipment side, the CELLFAB battery production line incorporates diverse interfaces such as RS 232, Fanuc PLC, Siemens S7-300, Siemens S7-1200, and others. Some equipment, like the Coatema coating machine, has a fixed/static IP address predetermined by the manufacturer, while others can obtain an IP address through DHCP. Additionally, certain equipment supports the OPC UA protocol (e.g., Coatema or Saueressig calenders), while others utilize proprietary protocols (e.g., Binder climate chambers).

4.2 Target state (Requirements analysis)

In order to develop a user-friendly data collection system, specific requirements categorized into functional and non-functional types shown in Figure 3, are presented in this chapter. In terms of *Device & Tag Visualization*, the system should display a selection of connected devices and their available tags, including their online status, names, update counts, last known values, and timestamps. Filtering methods for tags should be provided, allowing users to create parameters from the displayed tags. For *Parameter Selection & Annotation*, the system should store a list of parameters referring to device tags, annotated with user-specified names, sampling intervals, units of measurement, and descriptions. Parameters should be grouped into machines, with the ability to add, modify, and delete machines and associated parameters. Regarding *Data Collection*, the system should query parameter values at their specified sampling intervals, collect and store the data points in a structured format, and associate each measurement with the corresponding parameter and timestamp. It should also display the status of data collection for each parameter and machine. In terms of *Data Management & Export*, the system should provide structured formats for exporting selected measurements that can be easily imported by programming languages and spreadsheet applications. It should also allow users to organize measurements into batches, defined by unique names and containing tuples of machines, start and end times. Additionally, an API may be provided to allow access to the data base.

Functional		R1: Device and Tag Visualization • Enable identification of relevant tags with convenient filtering function and live parameter values
		R2: Parameter Selection and Annotation • Identify, filter and organize machine tags into descriptive and enable annotation capabilities
		R3: Data Collection • Continuously record all parameters for later research into a systematic and standardized database
		R4: Data Management and Export • Organize measurements into batches and export them in a standardized format (such as .csv or similar)
Non-func		R5: Usability • Offer a streamlined, device-independent user interface with a focus on relevant features and parameters
		R6: Flexibility and extensibility • Design as an extensible open-source application capable of integrating future machinery or devices

Figure 3: Overview of functional and non-functional requirements

In addition to functional requirements, non-functional requirements play a crucial role in the user experience, adaptability and reduction of training requirements. These non-functional requirements ensure that the application is user-friendly, adaptable to evolving research needs, and easily maintainable and extensible. For *usability*, the application should minimize training requirements and focus on relevant features. Interactions should be automated, and the user interface should update tag and parameter values in a timely manner. The application's user interface must be accessible over a computer network without requiring the installation of specific software on client devices. It should also minimize external dependencies and configuration requirements for quick setup. In terms of *flexibility and extensibility*, the application should be able to integrate future devices without modifying its source code. It should be simplified for improved maintainability and extensibility. The source code should be available and modifiable by user organizations, and the application should use mature, documented, and actively maintained libraries.

4.3 System design

The system to be developed, based on the requirements outlined in Chapter 4.2, consists of three essential components OPC UA Server, Database and Data Management System. The OPC UA Server functions as the data collector and aggregator. The database serves as the storage for the collected data. The data is grouped in the database according to defined parameters and machines. Data Management System is a newly developed software component. It undertakes several tasks to provide a user-friendly interface for managing the data, specifically targeted towards battery production researchers. A schematic illustration of the system can be seen in Figure 4. It serves as a user-friendly interface for managing the data within the system.

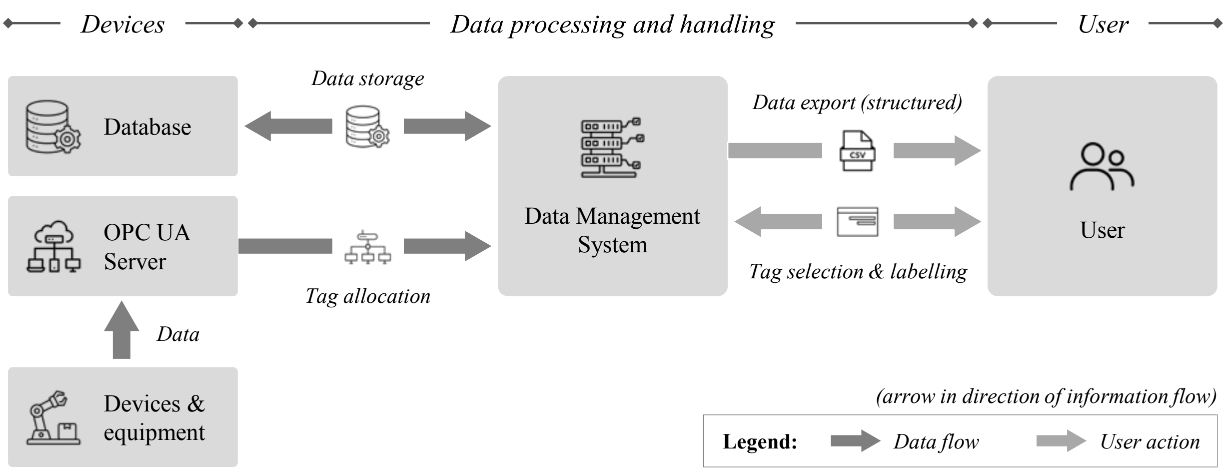

Figure 4: Overview of the structure and core functionality of the Data Management System and periphery

First, it provides an interface to manage the connected data sources via the OPC UA Server. Researchers can define and monitor these sources effectively. The data management system also enables the creation of new data points in the database and facilitates the seamless transfer of data from the OPC UA Server. Researchers can add new data points as required and ensure the continuous flow of information for analysis. Furthermore, the Data Management System offers a data provisioning feature, allowing researchers to select specific facilities, parameters, and time frames of interest. It then extracts the requested data and provides it in a convenient CSV file format. Lastly, data management system includes visualization capabilities, providing researchers with real-time insights into facility statuses and live machine data. This enhances their ability to monitor and analyse production processes effectively. Overall, the Production Pilot acts as a user-friendly, comprehensive interface for battery production researchers. It simplifies data management tasks, enables easy data selection and extraction, and enhances the efficiency of production research activities.

4.4 Implementation

Based on the requirements outlined in Chapter 4.2, a data collection, management, and provisioning system were designed. The structure and components of the system can be seen in Figure 5.

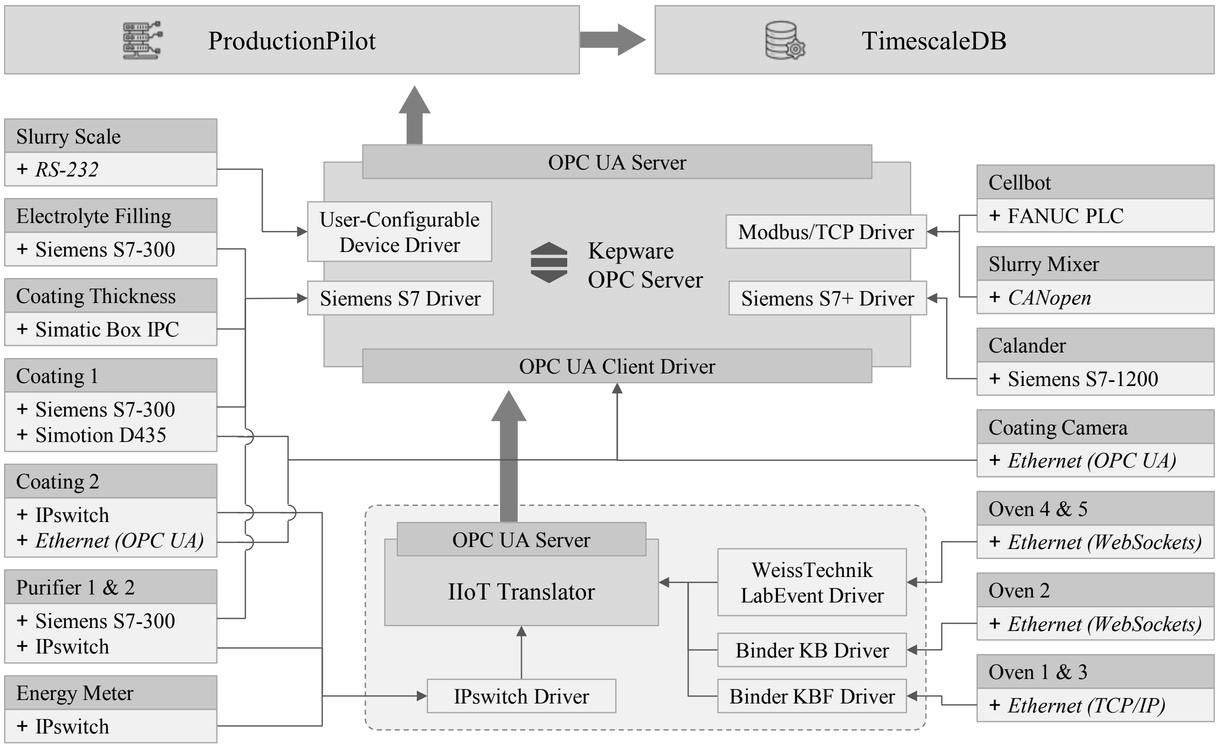

Figure 5: Data acquisition and collection architecture of the Data Management System

The machine integration, data acquisition, and aggregation were implemented using KepserverEX, a connectivity platform provided by PTC that is based on OPC technology. OPC UA was chosen as the communication protocol due to its ability to standardize data collection on the OPC UA standard. OPC UA is increasingly becoming an industry standard, enabling secure communication and has been a focal point in research projects such as DataBatt and Enlarge conducted at PEM. KepserverEX offers a wide range of drivers for machine communication, facilitating seamless data acquisition from various machines. For devices such as energy meters and climate chambers (Binder) that required specific communication interfaces, a custom-developed IIoTranslator was employed. To address the challenges associated with proprietary protocols, a custom adapter called IIoTranslator was developed. This adapter, depicted in Figure 5, functions as an OPC UA server and establishes connections with devices using their unique protocols. It then converts the data into OPC UA tags, ensuring compatibility with the OPC UA standard for a range of target devices. A suitable database was selected to store the acquired data. Factors such as data volume, data structure, and query performance were considered during the selection process. The chosen *database* provides efficient storage and retrieval capabilities for the collected data, ensuring data integrity and accessibility. As shown in Figure 5 a TimescaleDB database, was used. TimescaleDB is an extension built on PostgreSQL and is specifically designed for managing time-series data. The decision to select TimescaleDB for the application is based on the advantages it offers, particularly its foundation on PostgreSQL. This allows TimescaleDB to inherit the benefits of its parent relational database management system (RDBMS), including SQL support, scalability, and reliability. The support for standard SQL queries in TimescaleDB is expected to reduce training requirements, as SQL is widely used in the industry and developers are likely to already be familiar with this query language. Another advantage of using a widely adopted RDBMS database is the availability of support in the Java Persistence API (JPA) framework. A *data management system* was developed as the user interface for data collection and provisioning. This system serves as a centralized platform for users, specifically battery production researchers, to interact with the data acquisition system. It allows users to manage connected data sources, create new data points in the database, perform data pipelining from the OPC UA server to the database, and extract data based on user-defined criteria. Additionally, the data management system provides visualization of equipment status and real-time machine data, enhancing the user experience and facilitating efficient data exploration and analysis. The Production Pilot software acts as an OPC UA client in the system as shown in Figure 5. For data collection and aggregation, ProductionPilot has a way to select and semantically describe data points (tags). As the screenshot in Figure 7 in the appendix shows, the semantic description includes the assignment to a machine, naming, human readable explanation, and unit. In addition, the query rate for the respective tags can be determined. For direct access to the database, the program has a REST API. The REST API in ProductionPilot provides researchers with a standardized method to access stored information, ensuring compatibility and ease of integration with a future Python API. With its user-friendly design and integrated Swagger UI documentation, researchers can explore the API's functionality and perform direct testing from their web browser, facilitating efficient retrieval of data on machines, parameters, batches, and measurements. In general, ProductionPilot is web-based to allow access from different end devices with internet access. A central user administration is used to ensure that only authorized persons have access. The User Interface (UI) component of Production Pilot serves as the primary platform for users to interact with the application as can be seen in Figure 7 in the appendix. It displays the application's state and relies on various other services. The UI is designed to fulfil functional requirements such as displaying an overview of tags with their live values, implementing filtering methods for tags, allowing users to create parameters from tags, presenting a list of parameters grouped by machine for easy management, and showing a list of batches with options for creating, editing, and deleting them, along with an export functionality for downloading measurements in a user-friendly format.

5. Discussion and Conclusion

The research paper successfully demonstrates the digital connectivity of heterogeneous machine parks for research-scale battery production, showcasing the potential of advancing automation in data acquisition. By utilizing battery production as an example, the study emphasizes the importance of user-friendly systems for data acquisition, storage, and access to facilitate data-driven research. The proposed framework, exemplified by the PEM system at RWTH Aachen University, serves as a valuable blueprint for other facilities aiming to implement similar automation strategies. As future prospects, the authors suggest expanding the system to achieve end-to-end traceability for automated linking of process data with products and visualizing the data through dashboards to enhance decision-making capabilities. In addition, an extension of the system with ontologies that enable a semantic description and linking of the data is conceivable. This could simplify an automated analysis of the process data using AI. This advancement in data acquisition will undoubtedly drive improvements in battery production processes and contribute to the development of efficient and reliable energy storage solutions.

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Appendix

Figure 6: CELLFAB Battery Cell Production Line at PEM of RWTH Aachen University

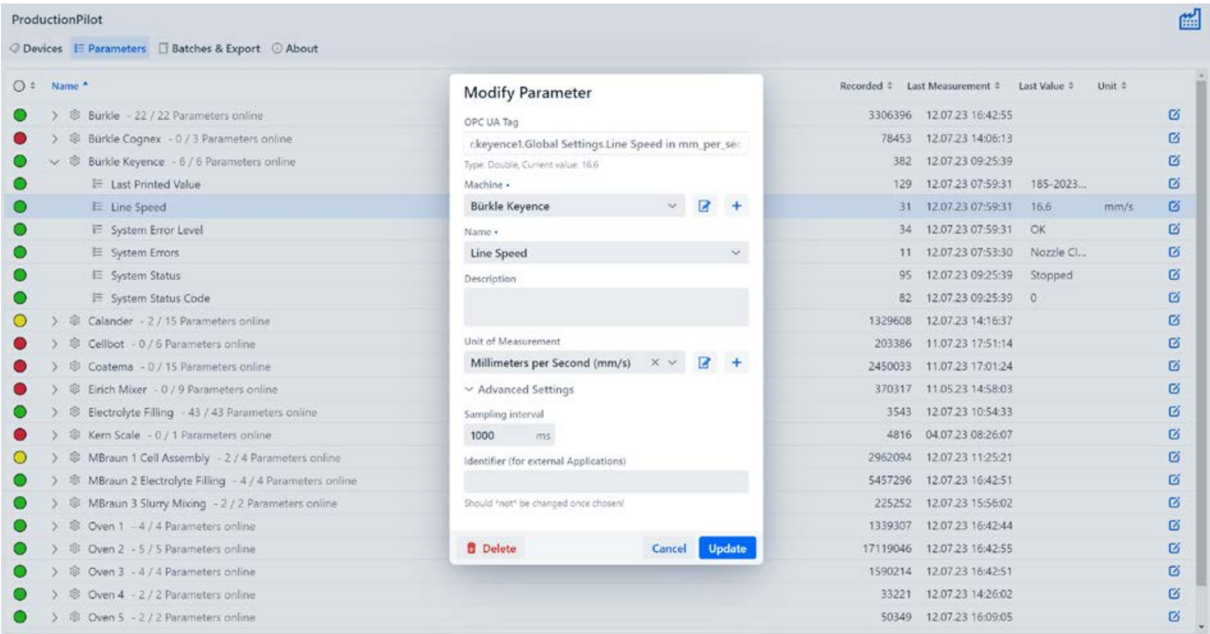

Figure 7: User interface of the Production Pilot data management system

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Biography

Achim Kampker *(*1976) is head of the chair "Production Engineering of E-Mobility Components" (PEM) of RWTH Aachen University and known for his co-development of the "StreetScooter" electric vehicle. Kampker also acts as member of the executive board of the "Fraunhofer Research Institution for Battery Cell Production FFB" in Münster. He is involved in various expert groups of the federal and state governments.*

Benjamin Dorn *(*1990) studied industrial engineering with a focus on mechanical engineering at RWTH Aachen University. He worked as a research assistant from 2017 and as a group leader from 2020 at the PEM of RWTH Aachen in the Electric Drive Production group. Since 2021, he has been part of the institute's management as chief engineer of the Production Technologies and Organization division.*

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