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Digital Twin in the Battery Production Context for the Realization of Industry 4.0 Applications

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Abstract

Due to the worsening climate change drastic changes in the transportation sector are necessary. Crucial factors for sustainable energy supply are reliable and economical energy storage systems. Associated with that is the development of giga factories with a capacity of up to 1000 GWh in 2030 in Europe (currently 25 GWh) for the production of battery cells especially for the automotive sector, which is one of the largest emitters of greenhouse gases in Europe. In addition to the required investments, high scrap rates due to unknown interdependencies within the process chain represent a central challenge within battery cell production. Another key challenge in series production is the product tracking along the value chain, which consists of continuous, batch and discrete processes. Because of its complexity the battery cell production industry is predestined for Industry 4.0 applications in order to meet the current challenges and to make battery cell production more efficient and sustainable. Digital twins and the use of AI algorithms enable the identification of previously unknown cause-effect relationships and thus a product improvement and increased efficiency. In this paper, the digital twin of a battery cell production will be developed. For this purpose, general requirements for the field of battery cell production are first determined and relevant parameters from the literature as well as from a production pilot line are defined. Based on the requirements and the selected parameters a corresponding structure for the digital twin in battery cell production is built and explained in this contribution. This provides the basis for measures to optimize production, such as predictive quality.

Keywords

Battery Cell Production; Industry 4.0; Digital Twin; Production Efficiency; Electromobility

1. Introduction

This paper presents a possible concept for the realization of a digital twin in the context of battery production. The focus lies on the digital twin of the battery cell and its components. Scrap rates in battery cell production are significantly higher than in other highly automated industries [1,2]. A major cause of this is a lack of understanding of interactions between process and product quality. A tool for the investigation and analysis of such interactions is the digital twin. The information model developed in this paper is intended to serve as the basis for the software implementation of a standardized digital battery cell twin. Among other things, this will enable standardized access to cell data and reduce the effort required to analyze large volumes of cell data. One challenge in the development of a digital cell twin arises from the fact that both the properties of the cell and the requirements for the digital twin change over the life cycle of the battery cell. As a result, the digital twin may differ in its characteristics compared to the real object and depending on the use case. In some cases, a real (interim) object can also be represented by several digital twins. In the context of product development, a battery cell twin is used to predict the subsequent cell parameters [3]. In the operation

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of a battery system of an electric vehicle, a battery cell twin can be used to predict the remaining lifetime based on current cell data or the twin can be used to control an optimal operation of the cell [4].

2. State-of-the-Art

2.1 Digital Twins in the Production Context

In the course of the digital transformation towards Industry 4.0, the digital twin is one of the frequently used terms in research and industry. However, there is no uniform technical understanding in the specialist community. It is apparent that there is no standardized digital twin and that its concrete form depends on the "positioning in the lifecycle, the use cases and business models" [5]. However, experts agree that, according to the original definition by GRIEVES, it is a virtual image of the reality [6]. The digital twin serves as a digital model for the abstract description of a class of physical units (e.g. product, machine, etc.) and its informations as well as the simulation for the prediction and optimization of the behavior of the performance characteristics [5]. A key requirement for digital twins, included in most definitions, is the ability to run scenarios and try out alternatives. These are often basic simulation models - in the case of production systems - event-based discrete flow simulation models [7].

Only in recent years the term simulation has gained acceptance in the production environment [8], whereas prior to 2017 it did not necessarily mean simulation, but rather the digital capture of all associated data [9]. This newer definition is adopted in the context of this paper. The digital twin is not to be confused with the digital shadow, which is referred to in other sources as a system for pure data acquisition without control by a simulation[10]. In the context of this paper, the digital shadow is not considered further.

2.2 LIB Manufacturing

The production of battery cells can be divided into the three steps of electrode manufacturing, cell assembly and cell finishing [11,12]. Figure 1 shows the different process steps and equipment for the production of lithium-ion cells in pouch format based on the pilot line of the eLab at RWTH Aachen University. The electrode manufacturing consists of a dry and a wet mixing process, in which the slurry for anode and cathode is produced. The slurry is coated onto current conductor foils (copper for anode, aluminum for cathode) and then convection or laser dried before entering the calendering process [13,14]. During the cell assembly, the electrodes are conveyed to the mechanical stamping line where they are cut into individual electrode sheets. The sheets are stacked (Z-folded) and contacted by ultrasonic welding. The cell stack is then placed in a thermoformed pouch foil and filled with electrolyte under vacuum and subsequently sealed. In the last phase, the cells proceed through the formation and aging step in a climate-controlled chamber, where they undergo the initial electrical loading and unloading, as well as quality testing over several days [15].

Figure 1: Process steps in battery cell production at the eLab of RWTH Aachen University

2.3 Digital Twins in LIB Manufacturing

In the field of battery production, there are currently only a few concepts concerning the digital twin, which will be analyzed in this section. KIES ET AL. identified, tracked and modeled 118 Parameters in the electrode production [16]. Example parameters are particle size, weight of the electrodes at the end of the production line and input materials. The aim of collecting these parameters is to create a traceability system which allows the production owner the best possible overview for each cell which results in a more realistic reflection of the battery systems' performance [17,18]. ROHKOHL ET AL. used the principle of a digital twin in the anode mixing [19]. They implemented a Gaussian Model which fitted to the actual dosage rates to their expected values during operation. After training and fitting the gaussian model to the actual dosage rate distribution the AI could approximate the expected distribution for a specific process parameter set. This leads to an increase in the mixing process stability. With the tool "Roboguide" from RobotStudio it is possible to create a digital twin of a cell stacking robot. Running a simulation of the digital twin of the process allows detecting collisions between robots and other objects, simulate the payload capacity of the robot and evaluate and optimize time taken for a sequence of movements in the cell stacking process [20]. AYERBE ET AL. review modelling approaches and analyze how they can be combined with data acquisition instruments and communications protocols in order to present a framework for building a digital twin. However, many challenges, including the setting of standards regarding models and data reporting remain unsolved [21]. Big players recognize the potential of the digital twin as well. Northvolt and Siemens reached a cooperation agreement to build an intelligent battery manufacturing plant and apply digital Twin to set up a product life management system based on closed-loop manufacturing [22]. Overall, the literature research revealed a missing product focus along the whole production chain. Furthermore, the predictive quality aspect of the cell within the digital twin is missing in the literature. What stands out in the research is a missing standard for the digital twin in the battery production. None of the sources established or used a standard in their works. This paper addresses this specific research deficit and presents a possible approach.

3. Information Model for a Digital Cell twin

The complexity of a digital battery cell twin differs greatly depending on what is to be achieved with the help of the twin. For example, a digitized BoM (Bill of Materials) that is updated automatically can already be defined as a part of the digital twin [23]. A digital BOM offers companies a simplified management of products and operations. Specific requirements are placed on a twin in the production context, which are explained below. In the first subchapter, the general structure of the digital twin and its information model is presented in detail. Subsequently, the general twin is subdivided into sub-twins based on the production requirements. This is required considering the intermediate products and corresponding quality. Finally, the connection between the digital battery cell twin and the plant twin is displayed.

There are already some publications dealing with the digital twin in battery cell production, such as KORNAS ET AL., TURETSKYY ET AL., AYERBE ET AL. and SCHNELL ET AL. [21,24–26]. In contrast to the first two papers, the present paper shows a structuring of data which takes place following a real object. For this purpose, sub-twins are introduced. On the one hand, this structured collection facilitates the interpretation of the data by humans. On the other hand, the standards simplify the feeding of data from production as well as the access to this data for analysis purposes. AYERBE ET AL. present a very comprehensive framework in which especially the modeling as well as the communication between plant and product are in the foreground. However, a concrete information model for the digital product twin is missing. In contrast to SCHNELL ET AL., a stronger structuring of the data takes place in the digital twin. In general, the present information model also integrates geometric and material data into the twin, which are partially insufficiently considered in other twins. These enables a better comparability of the production data from different production sites.

3.1 Structure of the Digital Twin

A digital twin is supposed to monitor the real object throughout its entire life cycle, from the sourcing of raw materials to development and recycling (Figure 2).

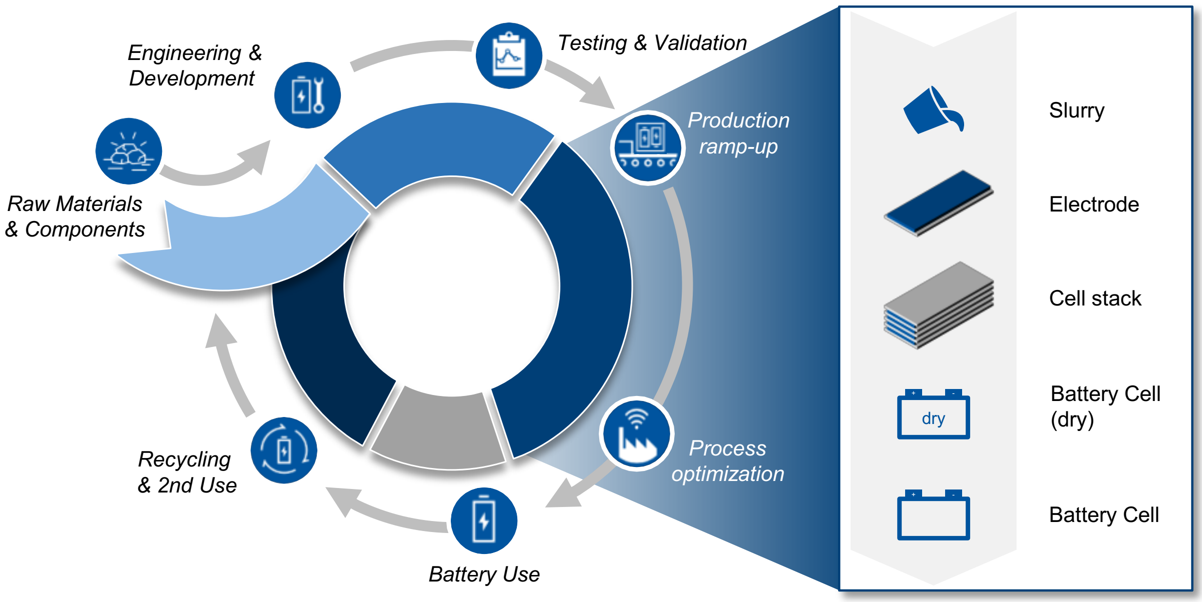

Figure 2: Battery Life cycle (left) and sub-twins during the production process (right)

The focus of this work is on the application of digital twins in the production context. The underlying use case is predictive quality. Predictive quality is a method that allows the prediction of the final product quality based on current information taken from the production process. For example, the quality of battery electrodes can be predicted already in the mixing process step, where the slurry is mixed [3]. Predictive quality allows errors to be detected at an early stage and reduction of defects as well as rework [27]. For battery production, this means that quality characteristics of the finished battery cell should already be determined and influenced in upstream production steps based on intermediate products. Predictive quality is of major relevance to battery cell production because rework is not possible in the production process. This is due to the many coating, wetting, cutting and joining manufacturing processes, which cannot be corrected in practice. Digital twins are particularly suitable for the implementation of predictive quality use cases. The basis of such a digital twin is a comprehensive and standardized data-based description of the real object [28]. In order to realize such a data-based description, an information model must first be created, which defines the structure for storing all relevant product data [29]. An example for the structure of an information model for a battery cell is shown in Figure 3.

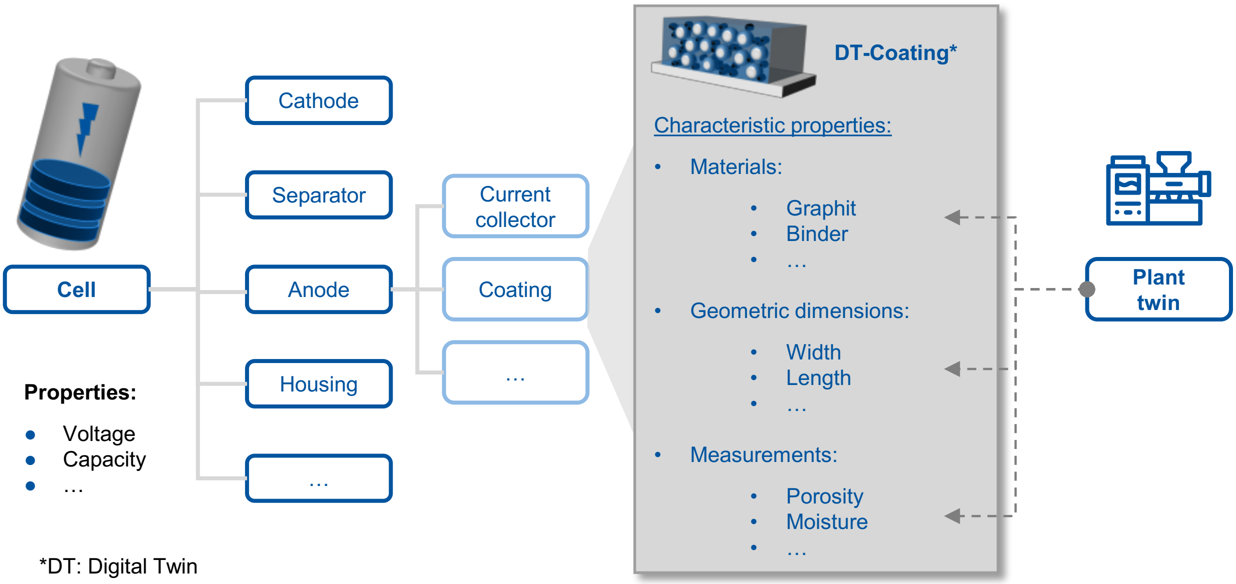

Figure 3: Information model for a lithium-ion battery cell and interface to plant twin

The data structure corresponds to the physical structure of the real object. In a first step, the battery cell object is divided into its central components. These include, for example, the two electrodes (cathode and anode), the separator and the housing. In a second stage, the components of the cell are further subdivided. For example, the anode consists of an anode collector and a coating. Specific product properties are assigned to the subcomponents at this level in a second structuring step. In this process, all characteristic features necessary for a complete description of the object are to be recorded. These characteristics can be divided into material properties, geometric characteristics, and measured values. Geometric features are defined as all features that characterize the dimensions and shape of the product. Material properties include all properties that describe the material, such as material type and proportions. The last category, measured values, includes all characterizing data of the physical object, which are measured during the process or are given based on data sheets. In particular, the category measured values was chosen for this information model with the background that the cell twin was developed for production. For this purpose, the twin is to be fed by data from production, which are measured inline or offline. The structure shown in Figure 3 represents a kind of container, which is successively filled with data during the production process. The system can be compared to that used in object-oriented programming. The battery cell represents a class. In this class, the cell characteristics are defined by attributes or instance variables, as in programming [30]. For each new produced cell now, an object of the class battery cell is created, which has the same attributes as the other objects of the class battery cell. The goal of this structuring is on the one hand to reduce the complexity of a cell-associated database, on the other hand, to realize a logical division of the data. The standardized storage of the data enables the implementation of APIs with the help of which simulation programs and AI-based analyses can be automated. In addition, the standardization enables automated allocation and retrieval of data. The modularity of the structure also allows the model to be extended if new parameters are added or removed. This may be the case, for example, with new technologies such as solid-state batteries. Another advantage of the information model is the ability to filter the stored data by specific components. For example, electrodes of several battery cells can be compared with little effort. A fixed structure also allows the definition of interfaces to other twins, such as those of intermediate products or the production infrastructure.

3.2 Subdivision into Sub-Twins for the Requirements in Production

For the digital twin of battery cells in the production context, a subdivision of the cell twin into so-called sub-twins is reasonable. This is done on the background that the semi-finished products such as slurry or electrode stacks change fundamentally in cell production until the end of cell finalization and thus the data-based description also undergoes fundamental changes. For example, the data-based description of slurry, which is at the beginning of the process, is not possible with an information model for a coated electrode or even finished battery cell. However, the sub-twins are not to be considered in isolation but serve as suppliers of data for the final cell twin and are thus part of it in the overall context.

Thus 5 sub-twins in the course of production can be defined as shown in Figure 2: Slurry, electrode coil, cell stack, cell (dry) and battery cell. A new information model is necessary in each case when the object properties change fundamentally, for example through the addition of a new component. In the step from the electrode coil to the cell stack, for instance, the separator is added. This structuring is important because data is transferred, added, or dropped from one sub- twin to the next until the final battery cell twin is created. For further instance, the particle size distribution of the twin slurry is transferred to the twin electrode, but the characteristic slurry viscosity does not longer exist in the case of the (dried) electrode. The stacking accuracy is an example of a characteristic that is added in the stacking process step and did not exist previously. To explain it again in the image of object-oriented programming, the individual sub-twins represent different classes, which are characterized by different attributes. Beyond that a subdivision is important, to be able to establish connections between different characteristics. For example, the coating no longer has a (relevant) viscosity, but conclusions can be drawn from the quality of the coating to the viscosity. This requires linking the data set with simulations.

3.3 Connection Cell Twin Plant Twin

The basis of a digital twin is the data set available for it. To create this, the database of the twin must be filled with corresponding data according to the structure of the information model from Chapter 3.1 and 3.2. Sources used as input can be data sheets, CAD models, measurement results (offline and online) or process parameters. In order to be able to transfer the data to the twin, corresponding interfaces must be defined for the twin of the battery cell or its intermediate products.

For the exchange of data with the production infrastructure, a standardized structured database and corresponding interfaces must also be available on the production side. A corresponding information model could have the structure shown in Figure 4. This can also be the basis for a digital plant or process twin.

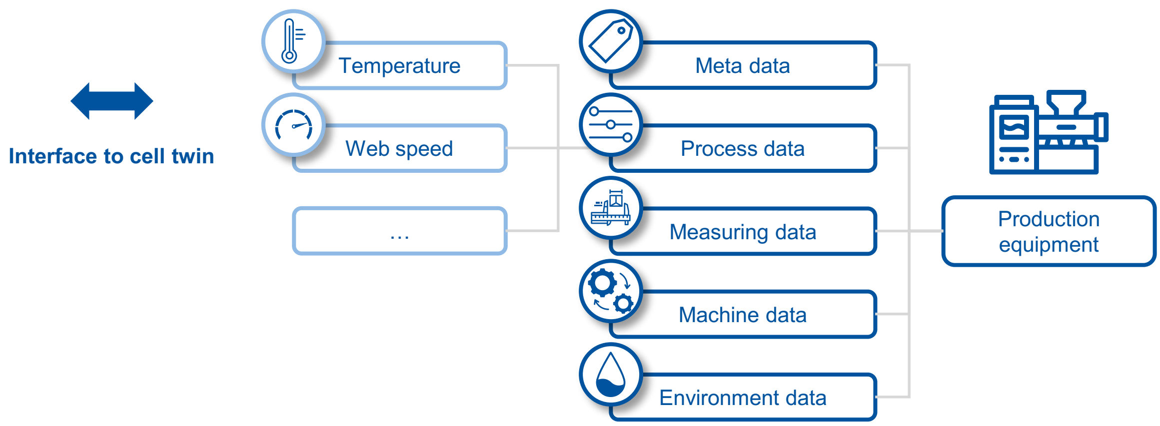

Figure 4: Potential Data model for production equipment (plant twin) and interface to battery cell twin

The two categories of process and measurement data are particularly relevant as an input for the product twin since these data have a direct influence on the product or characterize it. Process data is defined as data that can be set on the machine and characterize the process, such as temperature, web speed or mixing time.

Measured data are features that serve to characterize the processed product, such as coating thickness or viscosity. Data of other categories play a subordinate role for the predictive quality application, which is why they will not be discussed further here.

4. Using the Twin in Battery Cell Production

The information model can be converted into a defined data structure using the Asset Administration Shell (AAS). This is intended to become the standard for the implementation of digital twins within the framework of Industry 4.0 [31]. It provides the possibility to describe an object digitally. In addition, the AAS has interfaces so that instances can be mapped to OPC UA or MQTT. The AAS Explorer is available for free on GitHub.

One potential use case for the digital cell twin in association with predictive quality, which has been established prototypically in a battery production line at the RWTH Aachen University, is the prediction of coating thickness in electrode production (Figure 5). To meet the requirements of the development departure that defines certain cell specifications and to be able to guarantee a certain quality, the thickness of the coating must be homogeneous and within fixed tolerance limits. The homogeneity and thickness of the coating depends to a large extent on the quality of the used slurries as well as the coating equipment. In order to reduce rejects at an early stage, the quality of the produced electrode is to be predicted with the aid of simulations. The simulation is based on the data of the slurry twin as well as the plant twin. As plant twin in this context is meant a digital twin of the production equipment. If necessary, adjustments were made to the slurry (e.g., recipe) and the system settings (e.g., mixing speed) based on the simulation results. Integration of such a simulation on an edge device connected to the PLC could enable a closed loop process optimization. As a result, electrode quality is to be increased and scrap reduced at an early stage.

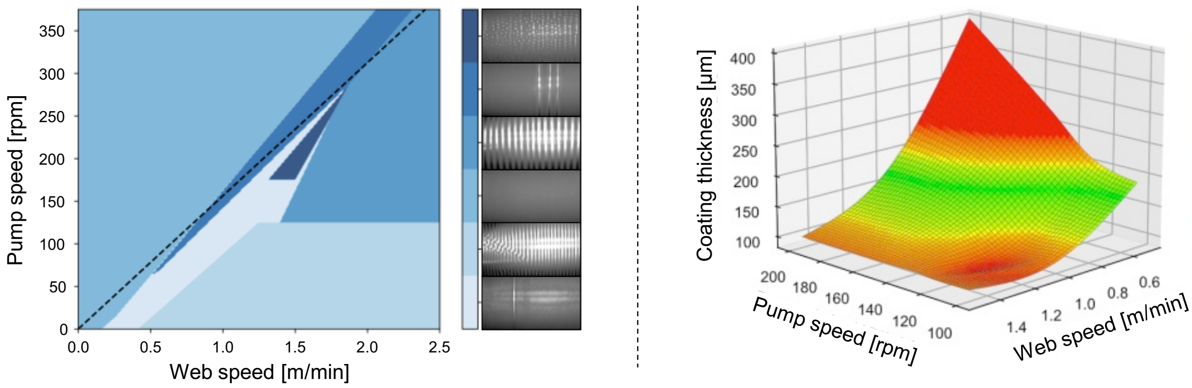

Figure 5: Machine learning based prediction of coating patterns (left) and coating thickness (right)

5. Conclusion and Outlook

This study has shown how production oriented digital twin approaches can be used to implement predictive quality battery cell production. The presented paper defines individual (sub)cell-twins that represent different intermediate products in production. These specific attributes of the sub-twin are assigned to in a structured way. However, in order to have a complete digital battery cell twin, an interface to the plant twin is necessary. With this information, the processed product can be fully characterized and provides the basis for prediction of product quality in subsequent process steps is possible. The use of digital twin models enables the determination of effects of individual parameters on cell quality and the corresponding product characteristics. With the help of this approach, an adaptive production control can be implemented in a use-case. In addition, the simulation of cell quality during production serves as a decision-making basis for the introduction of changes in production. As a next step of research, the approach should be implemented and tested in further battery production situations on a pilot scale. If the results from the pilot manufacturing runs are reproducible in industrial production environments, the approach would help to improve the product quality and decrease the scrap rate. For the implementation of the predictive quality use case, the information model presented here must be adapted depending on the production equipment and the existing database. One challenge is the accuracy of the simulations. These must be able to predict real processes with high accuracy. Otherwise, the adjustments to the production parameters will not lead to quality improvements. A closed loop control of the machines based on simulation results also requires direct and automated access to the machine control system, which represents a challenge from a safety perspective.

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Biography

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