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Holistic Approach for Digitalized Quality Assurance in Battery Cell Production

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Abstract

In this paper, we introduce a holistic approach to consider quality assurance (QA) for battery cell production (BCP). The framework, the explanation of the individual components as well as their interfaces and dependencies, and a detailed description are presented. Firstly, the level of necessary data (e. g. provided by online and out-of-line measurement systems) for the inspection of quality is presented. The aggregation of the recorded data as well as their tracing are ensured by the realization of a traceability system. Subsequently, by defining a suitable intelligent quality gate system, QA mechanisms are implemented and an active influence on production – e. g. by adaptive process control or identifying and reducing negative influence of cause-effect relationships – is aimed at. Finally, optimization of BCP in terms of product quality and its sustainability will be enabled. The evaluation of the demonstrated approach in practice is outlined based on an exemplary process of BCP.

Keywords: Battery Cell Production; Industry 4.0; Sustainability; Quality Assurance; Traceability.

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1. Introduction & fundamentals

Lithium-ion batteries (LIB) have established as a key technology for a wide range of applications due to their power and energy density [1, 2] . Both cell manufacturing process and materials used for production are critical to the quality of LIB [3]. Holistic QA is necessary to improve quality and reduce scrap [4]. For QA, a variety of procedures and technologies exist that are capable of testing defined aspects at specific stages in production. An aggregation of these aspects to be used for comprehensive QA is missing so far. One challenge in implementation lies in the characteristics of BCP itself: inter-linked process steps coupled with different manufacturing processes [5]. This complexity can result in a supposedly irrelevant quality characteristic leading to defects and deviations in the manufactured products over several manufacturing processes. Causes for deviations are not only in the corresponding process step, but also in the upstream processes [6]. Therefore, by improving the individual process, the cause cannot be eliminated, and the production process cannot be optimized holistically. For this reason, the entire process chain should be considered to increase quality [7]. Traditional methods of quality management are often focused on the investigation of individual processes and they reach their limits when considering the process chain as a whole [8].

For many applications that rely on mobile energy storage, LIB has emerged as the best solution in recent years. In terms of cell type, a distinction is made between round cells, pouch cells and prismatic hardcase cells. The production of the cells is divided into three main process steps: electrode production,

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cell assembly and activation or formation [9]. In electrode production, the production for anode and cathode follows the same process steps. The electrode foils are coated with a paste of active materials – the slurry – dried, cut into narrower electrode strips (slitting process) and finally dried again under vacuum [10, 11]. Subsequently, in the assembly processes, the manufactured electrodes are placed together with separators into the – depending on the cell design – respective housing. Finally, the cells are sealed, filled with electrolyte, and formed.

2. Related work

2.1. Measurement systems in BCP

In BCP, the use of measurement systems is essential to monitor the various production steps by recording product characteristics, process, and environmental parameters [12]. This increases the transparency of the process, allowing early detection of rejects and a better understanding of the process [13]. Measurement systems not only fulfil the task of measuring but can also be seen as a value-adding factor by increasing efficiency, thus optimizing, and stabilizing the production process [12]. Measurement methods are subdivided according to where the measurements take place, with a distinction being made between out-of-line and in-line measurement methods. Out-of-line methods involve taking random samples from the production process and analyzing them in the laboratory. This allows detailed analysis, but disadvantages are the time-consuming process, the risk of non-representative results and the fact that no direct active process adjustment can take place. In contrast in-line measurement methods allow continuous monitoring in the production process, enabling to perform quality control during production. In general, the measurement is fully automated and continuous, and only non-destructive and non-contact methods are used. Ideally, 100 % of the intermediate product are inspected [12, 13]. The disadvantage is high costs for suitable measurement systems, given the need for high throughput and accurate measurement results. Further challenges are the large volumes and rates of data generated by the large number of measurements and by imaging techniques, which require a data handling strategy, including data processing, data archiving, etc. The variety of inspection characteristics influences the quality in different ways and making it necessary to define tolerance ranges and defect types with respect to safety and performance critical characteristics. The challenge is to achieve the highest possible quality standards with the lowest possible reject rates [12, 13].

2.2. Traceability in BCP

Traceability systems are based on the main elements identification, capture, as well as data acquisition and aggregation of critical product-related data. The main goals encompass the creation of transparency and solutions for supply chain safety [14–16]. A properly implemented traceability system enables the improvement of production quality and the decrease of scrap rates [15]. However, the implementation of traceability systems in BCP is challenging since the physical marking of intermediate products should not have negative impacts to the quality of battery cells and its intermediate products [17]. Furthermore, the process chain in BCP consists of discrete and continuous process steps. Therefore, the granularity of the batches transforms during the manufacturing process. To enable intermediate products to be identified along the entire process, new identifiers may be applied. The main challenge for identification lies in the continuous electrode production, since the object granularity changes along the process chain and the position and size of for possible identifiers (e. g. on electrode foil) is restricted [15]. For ensuring identification, related work analyze different identification methods and their applicability in particular process steps [18, 19]. From a digital perspective, further related work proposes to group specific process steps in which the batch structure is stable. Based on this process clusters, they present the digital shadow for enabling traceability in battery production. However, there is not a standard yet that is simply applicable for implementing traceability in BCP, as identification of intermediate products is challenging, and the level of detail that should be depicted in the traceability system depends on specific requirements. [15]

2.3. Quality gates in battery production

In literature, a point between two production processes, which is used to make decisions regarding quality-relevant aspects, is termed a quality gate (QG) [20]. Towards the expansion of traditional QG *Schnell et al.* developed a modified approach for BCP that generates additional knowledge, especially regarding process-product correlations and interdependencies between failure causes, by using modified FMEA and DoE methods to consider the complete process chain [21]. The modified QG approach for BCP was further evolved by *Turetskyy et al.* and *Filz et al.* into a virtual QG approach to identify further root-cause effects and apply the option of a real time optimization [22, 23]. For this a variety of data from the physical world such as machine and product characteristics as well as internal and external influences are acquired to capture the current state of the whole manufacturing process. The data can be acquired from different manual (e. g. offline spreadsheet) or atomized (e. g. sensors or control software) data sources. Due to the emerging variety of data sources and data formats the data needs to be standardized and stored, corresponding to the intended usage. In the cyber world, the prepared data serves as a basis for machine learning and data mining methods to select, analyze and predict intermediate product features (IPF) and final product properties (FPP). Regarding this, simulations and models can be used to generate new information based on the aggregated data. The results are evaluated, visualized and decisions for the physical world are derived and adapted. In this way, it is possible to analyze or predict the state of the physical product regarding the whole process chain in real time and intervene in the current state by adjusting process parameters or optimizing processes

[12, 13]. In addition, there are also approaches by *Thomitzek et al.* and *Kornas et al.* that present simulative determination and multi-criteria parameter optimization based on a superficial framework [24, 25]. However, the validation in all process steps (e. g. electrode production) is still pending and a transfer to high througput production must still be evaluated.

2.4. AI for QA in BCP

To improve the cost structure and increase the efficiency of the manufacturing process, AI is offering a promising approach in current research [26–29]. In the field of QA, AI is used for process mining in order to understand critical process parameters [27, 30]. Hence, this knowledge can be used to monitor the manufacturing process and assure the quality of the product [31]. One step further, the product quality can be predicted in an early phase of the manufacturing process [28]. Other examples of an AI based QA are image-based monitoring solutions for the electrode manufacturing process. *Choudhary et al.* proposed the deep learning based YOLOv5 algorithm to detect defects on the surface of the electrodes [29]. However, AI-based quality solutions need a well-structured data basis from various manufacturing steps. Depending on the problem statement, data is required from a single process step (e. g., machine optimization) or a combination of multiple process steps (e. g., predictive quality [28]). Hence, collecting data in a sufficient quantity and quality is a prerequisite for any AI-based task [30]. Unfortunately, collecting data of high quality and quantity comes with a variety of challenges. Common struggles are combining data that vary in their format, sampling-frequency or size coming from equipment of different vendors. However, an additional problem is tracing data to the correct physical (sub-) product throughout multiple process steps [32]. For the application of AI in multiple process steps, the correct allocation of data to the physical (sub-) product is crucial. For example, in case of a single defect on the surface of the electrode that is recorded as an image through a visual inspection system after the drying process, tabular data from previous process steps (e. g. coating) must match the manufacturing time of the defect. This challenge can be solved by a holistic QA system, that automatically allocates process data to the physical (sub-) products based on a suitable traceability approach [32]. Therefore, a traceability system can provide a holistic data allocation throughout the whole manufacturing process, enabling multi-process AI applications.

2.5. Demand for holistic approach

To summarize, it is evident that the research area of QA in BCP is currently being intensively researched from various perspectives. However, the fulfilment of these partial aspects also only partially enables optimization of specific parameters of BCP. The digitalization of BCP is subject to extensive research, e.g., *Wanner et al.* conducted a technology assessment, *Ayerbe et al.* performed an in-depth analysis on current status, challenges, and opportunities, and *Turetskyy et al.* derived data-driven applications [33–35]. However, a holistic approach to digitalized QA that focuses on linking the complex processes with a traceability system and the simultaneous implementation of virtual QG is missing. Only a holistic view of the aspects – measurement systems, traceability, quality gates, AI – and the transfer to a methodical procedure allow early and predictive QA in the sense of Industry 4.0. In this paper, we therefore propose such a holistic approach to QA in BCP.

3. Holistic approach for digitalized QA

To achieve a common understanding and definition of a holistic approach towards QA in BCP, we analyzed a wide range of existing definitions from different fields. In addition, several workshops have been executed with more than 30 experts and researchers – from the fields of QA, production processes, product design and digitalization. In these workshops, the various requirements for a holistic approach to QA were derived. Finally, four different sub aspects were identified as crucial: Measurement systems, traceability, quality gates and artificial intelligence (AI). The interfaces between the different areas were then investigated. This resulted in the characteristics and dimensions that a holistic approach must support.

3.1. Big picture

The result is a common understanding of a holistic approach to QA in BCP. This is shown as a big picture in Fig. 1. In this figure, the dotted lines indicate the data flow from the physical world (e.g., process parameters or measured quality criteria) into the digital world (bottom-up), the exchange with IT and OT systems via interfaces (left side, connected to traceability system), and the feedback into the physical world (top-down

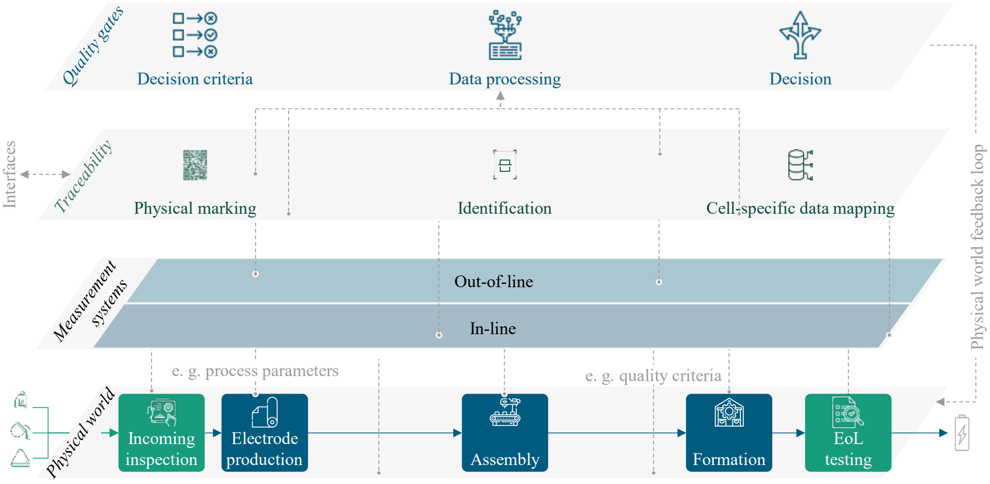

Fig. 1. Big picture: holistic approach for digitalized quality assurance in battery cell production

on the right side). Starting in the lowest layer – the physical world – data from the various production processes as well as incoming goods inspection and end-of-line testing (EoL testing) are acquired to create a digital representation of the product – a digital twin. According to *Stark et al.*, "a digital twin is the digital representation of a unique asset, that compromises its properties, condition and behavior by means of models, information and data." [36] Data are related to process parameters, information on input materials, disturbance variables, environmental conditions, and quality characteristics. Suitable measurement systems (second layer) are used to measure the quality characteristics by performing in-line or out-of-line tests on the product. By realizing a traceability system (third layer) using unambiguously marking the (intermediate) products with laser-applied data matrix codes, data can be assigned down to the smallest granularity (in the context of BCP, to the individual electrode sheet). Through continuously identifying the (intermediate) products via unique identifiers, data from downstream processes can be assigned in a cell-specific manner. This assignment allows the implementation of intelligent quality gates (top layer) based on the aggregated database per unit. For this purpose, decision criteria are initially defined. Using appropriate data processing – which can vary depending on the quality gate and can range from simple comparisons to calculation using machine learning algorithms – decisions can finally be made. Via feedback loops into the physical world, an active optimization of the quality of the products is made possible beyond simple QA.

3.2. Measurement systems for quality-related data acquisition

As shown in Fig. 1, measuring systems record quality-related data along the entire process chain. To create a sufficient data basis, it is necessary to consider different granularities due to the large number of processes. A challenge is the time-related linking of in-line and time-delayed out-of-line measurements. To evaluate the (intermediate-) products based on data within the quality gate concept, it is necessary to allocate the exact position using a traceability system. For this purpose, the recorded data is linked to a identifier and transferred to a database. This requires suitable interfaces such as OPC UA and data archiving strategies, as it is described in *Ayerbe et al.*, describing OPC UA as "an example of standardized communication protocols." [34]

3.3. Traceability enabling cell-specific data allocation

In addition to the actual marking and identification of (intermediate) products and the resulting allocation on the data side, which is a subject of current research (cf. [37]), this paper focuses on the requirements and conditions of the traceability layer to the measurement technology and the quality gates.

For realization, it must be ensured on the traceability side, depending on the quality gate under consideration, that the following most important factors are fulfilled:

- Process-related provision of the target values and tolerance ranges required in each case
- Provision of necessary cross-process information
- Provision of the necessary information for classifying the quality (depending on the battery cell design)
- Timely provision of the information
- Integration of historical data necessary for the decision
- Batch and single unit data
- Positionally accurate indication of defects

On the other hand, it is necessary that the following most important factors are fulfilled by the layer of measurement systems to ensure that the traceability system can forward needed information for decision making in the QG layer:

- Data formats that are as standardized as possible
- Granularity of data that meets the requirements of the respective quality gate
- A high level of data quality (to ensure timely provision for decision-making, without further data pre-processing steps)
- A frequency of data acquisition consistent with the specific demands
- Assignability of samples from out of line measurements

3.4. Quality gates as part of holistic approach

Within the holistic QA approach, which is described in this paper, the virtual quality gates (vQG) take a central role for the control of the system. They serve as an interface between the digital and the physical world. Data that is recorded is to be converted into decisions in the digital world and then transferred back to the real environment of BCP by the vQG. Thus, at the physical feedback ports of a quality gate, a decision is made based on relevant quality cirteria. Two types of decisions can therefore be made. If the product is within the expected tolerance range, the intermediate product can enter the next process step. If this is not the case, it must be sorted out by means of suitable actuators. For this purpose, all relevant variables must be made available to the vQG by means of a holistic traceability system and evaluated on the digital side by means of suitable data analytic approaches.

3.5. Application of AI in holistic approach

The application of AI always requires a suitable dataset that represents the problem, which AI is expected to solve. Depending on the problem statement, data is required from a single process step (e. g., machine optimization) or a combination of multiple process steps (e. g., predictive quality [28]). Hence, collecting data in a sufficient quantity and quality is a prerequisite for any AI-based task [30]. For example, *Choudhary et al.* developed a model for defect detection on the electrode with few images and suspect that an increase of images would improve the performance of their model [29]. Unfortunately, collecting data of high quality and quantity comes with a variety of challenges. Common struggles are combining data that vary in their format, sampling-frequency or size coming from equipment of different vendors. However, an additional problem is tracing data to the correct physical (sub-) product throughout multiple process steps [32]. For the application of AI in multiple process steps, the correct allocation of data to the physical (sub-) product is crucial. For example, in case of a single defect on the surface of the electrode that is recorded as an image through a visual inspection system after the drying process, tabular data from previous process steps (e. g. coating) must match the manufacturing time of the defect. This challenge can be solved by a holistic QA system, that automatically allocates process data to the physical (sub-) products based on a suitable traceability approach [32]. Therefore, a traceability system can provide a holistic data allocation throughout the whole manufacturing process, enabling multi-process AI applications.

4. Application of holistic approach in BCP

In the production step of assembly, the individual cell components are transferred into cell housings, followed by filling with electrolytes and sealing. In the case of the pouch cell, the so-called stacks are formed from the periodic overlapping of single sheets of anode, cathode and separator [38]. Different technologies can be used for this, depending on the cell format and the materials used [39]. The example of the stacking process and the electrolyte filling will now explain the interaction between the QG and the other elements of the holistic approach. First, the QG is the basic framework for any decision. Thus, relevant quality decisions must be made on a generated data basis. Table 1 shows an extract of the relevant quality variables of the stacking and electrolyte filling process step. In addition to the quality parameters, various criticalities are also defined for the parameters. The gradation here ranges from very low to very high and has a direct influence on which parameters are to be made traceable in a traceability system. Thus, quality parameters with a criticality of medium or higher should be recorded by a traceability system and be able to be traced with single unit precision. This also applies to input, environmental, interference and process parameters not listed here. The corresponding evaluation of the criticalities is carried out corresponding to a methodology presented in [13]. There are various decisions which can be made for the quality variables presented. If the defects are irreversible and the target value and tolerance range could not be met, the intermediate products must be sorted out directly. If, on the other hand, the characteristics have an influence on the quality class of the cell, no specific decision must be made, but this information must be linked in the traceability system. In addition, there are also characteristics, which can still be adjusted by adaptive process control in the subsequent processes. In general, quality parameters such as thickness, geometric dimension and weight of the individual components are already monitored in the previous process steps [12]. Regarding the measurement technology to be installed, especially in the stacking process step, the focus is initially on the quality parameters, single stack accuracy between individual electrode sheets and overall stack accuracy, which must be carried out with a high degree of accuracy, otherwise this will have a negative impact on the battery's safety and performance [39, 40].

To monitor the accuracy of the positioning, optical systems such as high-resolution cameras are often used to inspect the cell stack. After housing, the cell stack is no longer visible for optical methods, which means that the final positioning inside the cell housing can only be determined by using transmission methods [41]. For example, out-of-line standard CT systems can be used to obtain a detailed 3D volume image of the internal cell structure [27].

Table 1. Excerpt of quality parameters and respective quality decisions for the stacking and electrolyte filling process of pouch cells

Quality Parameter	Process	Criticality	Decision
Single stack accuracy between individual electrode sheets	Stacking	Medium	Adjustment
Overall stack accuracy	Stacking	Very high	Sort Out
Voltage cell stack	Stacking	High	Sort Out
Angle accuracy	Stacking	Medium	Adjustment
Weight of cell stack	Stacking	Low	Nothing/Grading
Length of cell stack	Stacking	Very high	Sort Out
Cell stack width	Stacking	Very high	Sort Out
Thickness cell stack	Stacking	Very high	Sort Out
Coverage ratio of stack	Stacking	Medium	Adjustment
Resistance of cell stack	Stacking	Low	Nothing/ Grading
Weight of cell	Electrolyte filling	Very High	Sort Out
Leak tightness of cell	Electrolyte filling	Very High	Sort Out
Strength of the seal seam	Electrolyte filling	Very High	Nothing/ Grading
Equal electrolyte distribution	Electrolyte filling	Very High	Nothing/ Grading

5. Conclusion and outlook

In this paper, a holistic approach for QA in battery cell manufacturing, including a framework and the explanations of its individual components, has been presented. The big picture shows the strong interdependencies between measurement techniques, traceability system and quality gates. The elements of the big picture and their respective requirements have been presented. To demonstrate the application of the big picture in battery cell manufacturing, it has been presented based on the example of the stacking process. The example shows that the holistic approach can be used as a blueprint for developing automated quality gate systems in specific process steps by integrating the requirements of measurement systems, traceability, and quality gates in an early stage. Based on this holistic approach, automated quality control can be implemented using AI methods. This way, automated quality gates can be used in production that consider quality data of previous process steps for the decision whether this intermediate product should be processed further. Therefore, optimization of BCP processes can be performed focusing on efficiency and quality of the (intermediate) products. The need for sustainability of battery production is essential and approaches have already been discussed [42]. Further research should therefore aim at evaluating the holistic approach on further process steps as well as developing services and models that optimize the efficiency and sustainability of the BCP process using the implemented QA approach as a basis.

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