Proceedings of the DataNinja sAIOnARA 2024 Conference 81-83 DOI: 10.11576/dataninja-1179

Trustworthy Virtual Measurements in Battery Manufacturing

Lukas Krebs LUKAS.KREBS@WZL-IQS.RWTH-AACHEN.DE
WZL - IQS at RWTH Aachen University, Germany

Tobias Müller TOBIAS.MUELLER@WZL-IQS.RWTH-AACHEN.DE
WZL - IQS at RWTH Aachen University, Germany

Robert H. Schmitt ROBERT.SCHMITT@WZL-IQS.RWTH-AACHEN.DE
WZL - IQS at RWTH Aachen University
& Frauenhofer IPT, Germany

Abstract

The growing demand for electric cars necessitates an increase in battery production efficiency and cost-effectiveness. Through a reduction of the joint testing efforts an increase of productivity can be accomplished. To achieve the reduction, remain on a high level of quality standards and increase the informational content about current production the use of virtual measurements is examined. Ensuring the trustworthiness of virtual measurements is crucial for informed decision making, necessitating validation. This paper explores the requirements and challenges in battery manufacturing for implementing trustworthy virtual measurements. Two central requirements are identified to enable virtual measurements. Firstly, a traceability system based on the production meta-model is needed to track process parameters and quality characteristics. Secondly, a framework is proposed to facilitate reliable virtual measurements. The primary challenge for virtual measurement in battery manufacturing systems from the complexity of the process chain and products. It is crucial to assess how virtual measurements perform across various processes and to evaluate their transferability to different process parameters and products.

Keywords: Virtual Measurement, Uncertainty, Trustworthiness

1. Introduction

In 2019, the number of registered electric cars in Germany was still below 100,000. Five years later, over 1.4 million electric cars were registered in Germany, with a projected increase to ten million registered electric cars by 2030 [1, 2]. This structural shift also increases the demand for batteries for electric cars. To meet the growing demand, battery manufacturing must become more productive and cost-effective. However, high-quality standards for battery manufacturing must also be maintained. Current technology requires physical inspections throughout the battery manufacturing process, which are associated with high time and monetary costs [3, 4].
Virtual measurements can reduce the need for physical inspections, making battery manufacturing more productive and cost-effective [4]. In virtual measurements, quality characteristics are predicted based on process parameters. While early virtual measurements were conducted using polynomial equations, various machine learning algorithms are now used for quality characteristic prediction [5]. Virtual measurements are already employed in various industries, such as semiconductor manufacturing, metal processing, and textile technology [6].

2. Virtual Measurements

To make reliable decisions regarding product quality based on measurements, it is essential to consider both the measured quantity and its uncertainty [7]. Measurement uncertainty can be quantified using the Guide to the Expression of Uncertainty in Measurement (GUM) [7]. While measurement uncertainty in physical measurements is well-researched and applied in industry, virtual measurements often only specify the measured quantity without considering the corresponding measurement uncertainty [8]. In a production environment, the uncertainty of virtual measurements is crucial for trustworthiness. Thus, deterministic machine learning models used in virtual measurements should be replaced with models capable of indicating inherent measurement uncertainty.
Different measurement methods possess varying de-

grees of measurement uncertainty, influenced by different factors. While physical measurements are affected by environmental factors such as temperature, virtual measurements are comparably reliant on the available data for training and prediction. Thus to reduce measurement uncertainty, accurate mappings between process parameters and quality characteristics are necessary. Meta-models are used for this purpose, offering consistent data structuring throughout the production process [9]. This allows for virtual measurements at various points in the production process with sufficient automation of machine learning for virtual measurements and availability of relevant data.

3. Virtual Measurements in Battery Manufacturing

Battery manufacturing offers a broad application space for virtual measurements. Quality must be checked after individual process steps in both battery cell manufacturing and module and pack assembly. Early error detection is crucial to reduce quality variations and avoid scrap [10]. To make decisions regarding product quality with virtual measurements, first the requirements and challenges for the application of virtual measurements need to be examined.

Decisions must rely on trustworthy measurements, which can be quantified by measurement uncertainty. To provide virtual measurements with comparable measurement uncertainty to physical measurements, several requirements must be met. These include systematic recording of process data and important peripheral data. Not only data from the selected process but also from previous processes influencing the process parameters affecting the quality characteristics should be available. There must be a clear mapping between process data, peripheral data, and quality characteristics. Lastly, uncertainties in measurements must be provided at each data point. Thus, for trustworthy virtual measurements in battery manufacturing, a traceability system must be used, with a meta-model of production data underlying it.

Based on the data provided by the traceability system, virtual measurements can be conducted. Cramer et al. have already investigated how measurement uncertainty can be determined in virtual measurements analogous to the stages of the GUM[8]. They discuss the steps of formulating the measurement system, propagating uncertainty, and documenting virtual measurements. The presented principle utilizes various algorithms such as Bayesian Variational Inference or Markov Chain Monte Carlo to determine virtual measurement uncertainty. These algorithms can be employed for example in Bayesian Neural Networks or Bayesian Decision Trees to enable probabilistic forecasts [11, 12]. For documentation purposes, it is crucial to store the trained model and document the coverage intervals within which the measurement values lie. This framework lays the foundation for the application of trustworthy virtual measurements in battery manufacturing. However, the framework has not yet been applied to production data. Therefore, it should be extensively tested with different algorithms and potentially expanded.

Due to the complexity of battery manufacturing process chain, many different process steps are suitable for implementing virtual measurements [13]. Therefore, virtual measurements must be conducted at several relevant quality gates, increasing implementation effort. A dedicated machine learning pipeline for virtual measurement reduces implementation effort, enabling comprehensive testing. In addition, in battery manufacturing, there is a wide range of variations in both process parameters and final products [10]. Hence, investigating the adaptability of virtual measurement models for different process parameters or products is necessary. This would eliminate the need to create new databases when establishing or modifying product lines, thus reducing the effort for trustworthy virtual measurement.

4. Conclusion

In summary the main requirements to facilitate trustworthy virtual measurements in battery manufacturing are the traceability system based on the meta model of the production and the framework to conduct virtual measurements analogous to the stages of the GUM. With complex process chains, vast variety in products and process parameters there is a broad application field for virtual measurements. For a comprehensive review on the trustworthiness of virtual measurements in comparison to physical measurements in battery manufacturing multiple scenarios need to be examined.

Acknowledgments

The project on which this report is based was funded by the Federal Ministry of Education and Research under grant number 03XP0538.

References

[1] Cleverlog-Autoteile. Anzahl der elektroautos in deutschland im jahr 2023 und prognose bis 2030 (in 1.000), 15 November 2023. URL https://de.statista.com/statistik/daten/studie/1425629/umfrage/e-auto-bestand-prognose/. In Statista. Access on 02 May 2024.

[2] KBA. Anzahl der elektroautos in deutschland von 2006 bis januar 2024, 04 March 2024. URL https://de.statista.com/statistik/daten/studie/265995/umfrage/anzahl-der-elektroautos-in-deutschland/. In Statista. Access on 02 May 2024.

[3] Aslihan Örüm Aydin, Franziska Zajonz, Till Günther, Kamil Dermenci, Maitane Berecibar, and Lisset Urrutia. Lithium-ion battery manufacturing: Industrial view on processing challenges, possible solutions and recent advances. *Batteries*, 9(11):555, 2023. doi: 10.3390/batteries9110555.

[4] Paul-Arthur Dreyfus, Foivos Psarommatis, Gokan May, and Dimitris Kiritsis. Virtual metrology as an approach for product quality estimation in industry 4.0: a systematic review and integrative conceptual framework. *International Journal of Production Research*, 60(2): 742–765, 2022. ISSN 0020-7543. doi: 10.1080/00207543.2021.1976433.

[5] Christopher I. Lang, Fan-Keng Sun, Ramana Veerasingam, John Yamartino, and Duane S. Boning. Understanding and improving virtual metrology systems using bayesian methods. *IEEE Transactions on Semiconductor Manufacturing*, 35(3):511–521, 2022. ISSN 0894-6507. doi: 10.1109/TSM.2022.3170270.

[6] Yaxuan Zhang, Li Li, and Qingyun Yu. Virtual metrology for enabling zero-defect manufacturing: a review and prospects. *The International Journal of Advanced Manufacturing Technology*, 130(7-8):3211–3227, 2024. ISSN 0268-3768. doi: 10.1007/s00170-023-12726-x.

[7] BIPM, IEC, IFCC, ILAC, ISO, IUPAC, IUPAP, and OIML. Evaluation of measurement data — Guide to the expression of uncertainty in measurement. Joint Committee for Guides in Metrology, JCGM 100:2008, 2008. URL https://www.bipm.org/documents/20126/2071204/JCGM_100_2008_E.pdf/cb0ef43f-baa5-11cf-3f85-4dcd86f77bd6.

[8] Simon Cramer, Tobias Müller, and Robert H. Schmitt. Measurement uncertainty: Relating the uncertainties of physical and virtual measurements, 2024.

[9] Simon Cramer, Max Hoffmann, Peter Schlegel, Marco Kemmerling, and Robert H. Schmitt. Towards a flexible process-independent metamodel for production data. *Procedia CIRP*, 99: 586–591, 2021. ISSN 22128271. doi: 10.1016/j.procir.2021.03.112.

[10] Joscha Schnell and Gunther Reinhart. Quality management for battery production: A quality gate concept. *Procedia CIRP*, 57:568–573, 2016. ISSN 22128271. doi: 10.1016/j.procir.2016.11.098.

[11] Bakhouya Mostafa, Ramchoun Hassan, Hadda Mohammed, and Masrour Tawfik. A review of variational inference for bayesian neural network. In Tawfik Masrour, Hassan Ramchoun, Tarik Hajji, and Mohamed Hosni, editors, *Artificial Intelligence and Industrial Applications*, volume 772 of *Lecture Notes in Networks and Systems*, pages 231–243. Springer Nature Switzerland, Cham, 2023. ISBN 978-3-031-43519-5. doi: 10.1007/978-3-031-43520-1{\textunderscore}20.

[12] Giuseppe Nuti, Lluís Antoni Jiménez Rugama, and Andreea-Ingrid Cross. A bayesian decision tree algorithm, 2019.

[13] Andreas Aichele, Anselm Lorenzoni, and Jonas Lips. Method for the identification of process quality characteristics and suitable measurement systems in battery production. In Kai Peter Birke, Max Weeber, and Michael Oberle, editors, *Handbook on Smart Battery Cell Manufacturing*, pages 253–273. WORLD SCIENTIFIC, 2022. ISBN 978-981-12-4561-9. doi: 10.1142/9789811245626{\textunderscore}0013.