Predictive Maintenance in the Framework of Lithium-ion Battery Cell Manufacturing

Master Thesis: Development of a predictive maintenance concept for cell component production of lithium-ion battery cells in the automotive sector

In cooperation with the institute for factory automation and production from the university of Erlangen-Nuremberg

Table of contents

Integrating predictive maintenance in the framework of lithium-ion battery manufacturing

MANAGEMENT SUMMARY

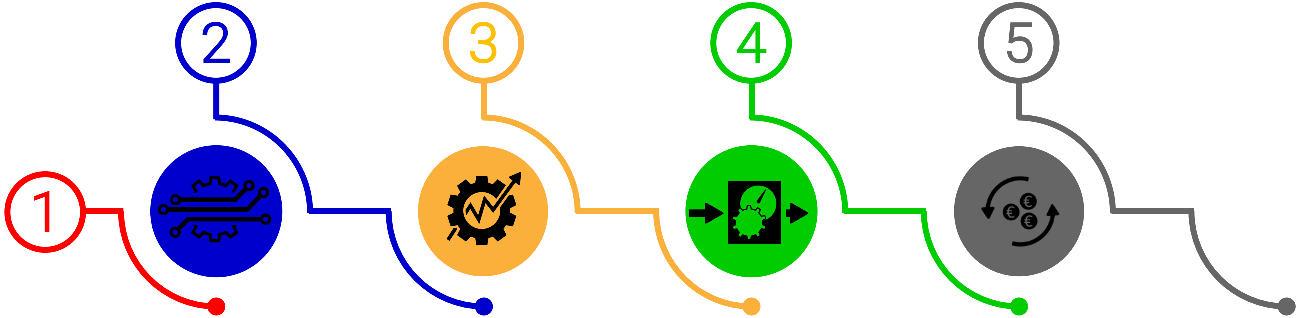
The increase in battery production including numerous gigafactories implies inevitable improvement in manufacturing efficiency and productivity. Due to this rapid development, integrated engineering systems become increasingly complex. This entails unanticipated faults in production processes that range from simple replacements to accidents, provoking fast costs in lost productivity as well as human and environmental resources. Damage induced or regular maintenance strategies according to the standard DIN 31051 do not exhibit capabilities in completely eradicating faults and thus no longer satisfy modern lithium-ion battery industry. Certainly, the reduction of downtime and maintenance expenses in the context of a zero-failure production is a critical aspect for a manufacturer in being sustainably competitive. Under the premise of a maximum achievable reliability in production equipment, a higher degree in automation of condition monitoring is desired. Therefore, this whitepaper investigates the potentials and trends of predictive maintenance strategies.

Integrating predictive maintenance in the framework of lithium-ion battery manufacturing

MANAGEMENT SUMMARY

The development of predictive maintenance is presented in a systematic concept, its technical challenges, and the potentials under the premise of intelligent data acquisition and processing. The concept includes scenarios of sensor selection and data acquisition, data preprocessing in data mining and decision support for advisory maintenance implementation. This offers a holistic understanding and instruction in all domains for industry practitioners. From the authors perspective it is important to counteract the complexity in battery cell manufacturing. In a hybrid approach, critical components are focused to be simulated and diagnosed with deep learning tools to extract microstructural information and predict impending failures, respectively. However, also process data including e.g. intermediate product information, provide failure inducing aspects. The proposed methods and techniques should enable the feasibility of diagnostic and prognostics in the framework of maintenance and deal with crucial data mining aspects.

The potentials that can be gained by integrating predictive maintenance



Advanced Condition Monitoring

By
- Integration of inline and online process tracing
- Continuous control of product quality

Enhanced product & process quality

By
- Extending life of equipment and process functioning
- Minimizing interference in equipment during operation

Increased equipment utilization

By
- Targeted selection of equipment that requires maintenance
- Shutting down equipment just before fault occurrence

Increased machine availability

By
- Production and maintenance schedule optimization
- Reducing machine down-times

Reduction of maintenance & service costs

By
- Organizing resources (e.g. service technicians)
- Catastrophe damage avoidance

References: Song et al. (2021), Toumi et al. (2019), Solle et al. (2017), Sai et al. (2019)

Table of contents

Predictive maintenance can be integrated in LIB production for increasing efficiency

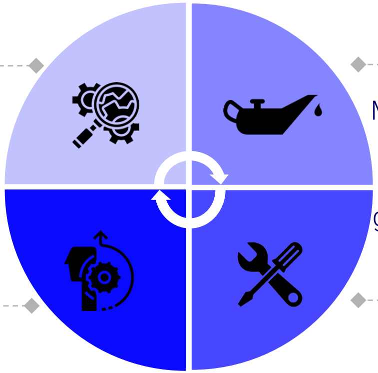
MAINTENANCE STRATEGIES

Inspection

Measures for determination and assessment of the current state of the machine's equipment (measuring, testing)

Service

Measures for maintaining the target state of the machine's equipment (e.g., cleaning, greasing adjusting, conserve)



Improvement

Measures for improving the systems current state and increasing the performance

Repair

Measures for retrieving the target state of a machine´s equipment (e.g., repair, replace).

PREDICTIVE MAINTENANCE - DEFINITION

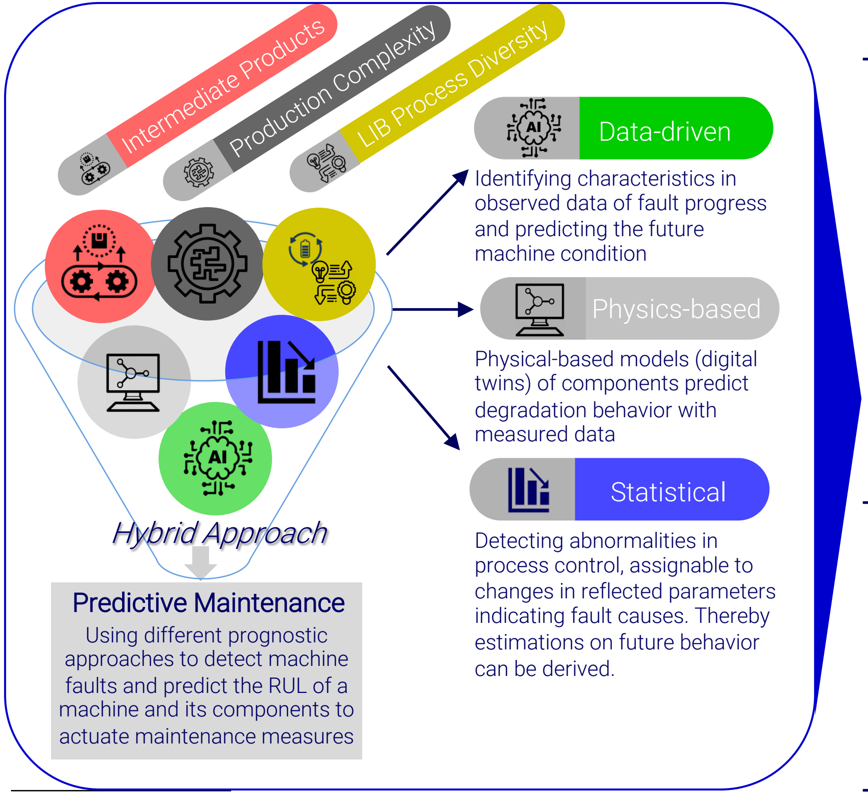
- Actual condition of machine equipment is determined by measuring process parameters.
- Comparing of specified functioning and actual functioning during operation
- If failure indications are recognizable, time is predicted until specified functioning is no more guaranteed

ADVANTAGES OF PREDICTIVE MAINTENANCE

- Shut down of equipment that requires maintenance just before failure
- Reducing maintenance costs by schedule optimization and damage avoidance
- Extending life of equipment and process functioning
- Increasing machine availability and reliability
- Minimizing interference in equipment during operation
- Reducing maintenance costs by avoiding catastrophe damage

References: Li et al. (2017), Sankavaram et al. (2020), Zhang et al. (2019), Shin et al. (2018)

A hybrid approach in predictive maintenance can handle the complexity of LIB cell production



	Physics-based	Data-driven (AI)	Statistical
Main Advantages	• Consideration of meso- and micro mechanism in components • Multidimensional variables are integrated (kinematic, dynamic mechanic structure) • Process metrics are modelled (e.g., thermal, chemical, mechanical, electrical) • Increasing information collection with virtual sensors in digital twin application	• Complex system behavior in machines can be modeled • Information from all levels can be processed (component-, machine-, process system level) • Ability to extract features form complex system data • Model are adaptable and flexible to multiple problems	• Economical and little effort regarding computational resources • Implementation is relatively easy • Usable for robust estimations in probability of average life span (for operation of mechanical components)
Main Disadvantages	• Not suitable for system-level prognostics and health management • High expert domain knowledge is required	• Component failure mechanism require expert understanding • Extensive training data are needed • Huge data amount for model training is needed	• Large amount of failure data and historical data is needed • Difficult to include environmental and actual operation conditions

References: Arena et al. (2022), Wang et al. (2017), Aivaliotis et al. (2019), Traini et al. (2021), Werner et al. (2019), Zhang et al. (2019), Zhang et al. (2022)

Table of contents

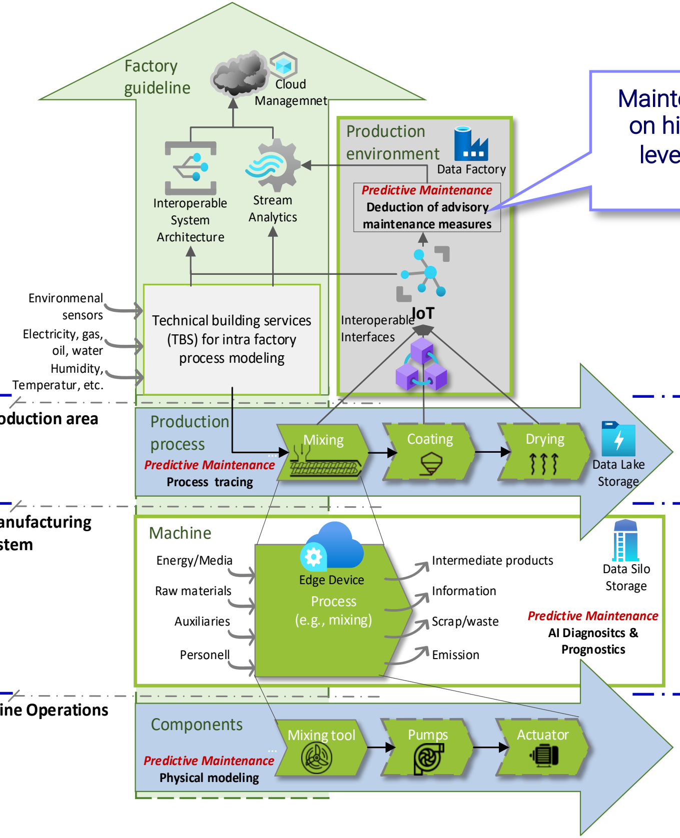
The system elements of the production architecture are structured to systematically acquire information for further data mining

4 Acquisition of data from production environment integrating the collected production process data

3 Consideration of interdependent process influences

2 Data acquisition of all machine intern processes and all inputs and outputs

1 Simulation of components to generate digital twin



Maintenance advisories on hierarchical higher levels of production system

Data processing through interoperable system architecture for data analytics

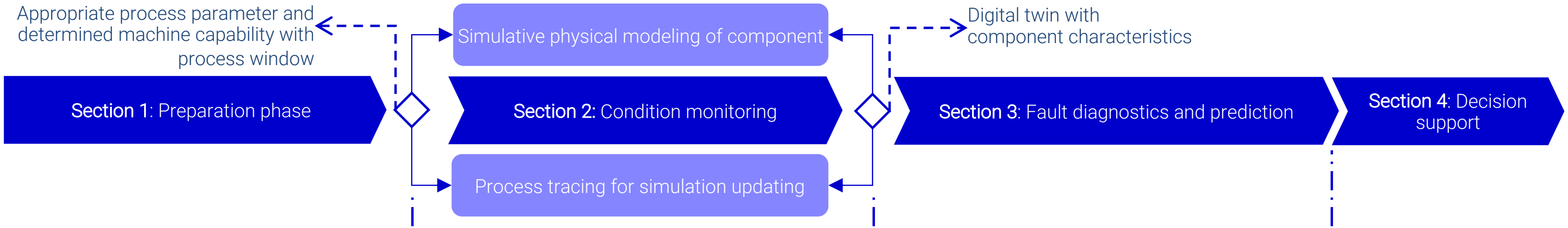
Process data tracing and collecting information in data lakes over production units

Machine data processing in “data silos” from edge devices to diagnostics on failures for predictions

Data acquisition e.g., Mechanical stresses (tensions, abrasion), kinematic/dynamic

The real time operation conditions can be considered by updating the physical simulation and separating deep learning diagnostics for handling LIB production complexity.

PROCESS OF THE PREDICTIVE MAINTENANCE APPROACH



Description of approach

1. **Production process analysis:**
   - Process Inputs
   - Product quality influencing factors
   - Process interdependencies
   - Process steps with critical components
   - Relevant parameters of the critical process
2. **Conducting parameter studies for identifying machine behavior**
3. **Determining process behavior**

Mathematical-physical modeling of critical components:
- Modeling of **dynamic behavior** based on kinematic and structural model
- Modeling **virtual sensors** for extending information acquisition
- Considering **relevant modelling parameter**

Statistical process tracing for:
- **Synchronizing** physical simulation and creating **digital twin** information
- Detection of **process inconsistencies**, indicating machine degradations

Fault diagnostics:
- Signal and data preprocessing (**data cleaning, -filtering**)
- Feature extraction and selection
- **Health Indicator** construction
- Using deep learning for **machine fault diagnosis** (incl. model training and validation)

Fault prognostics:
- Reflection of actual **machine state of functionality**
- **Fault analysis** by using expert domain knowledge
- Implementation of deep learning techniques for **RUL prediction** (incl. model training and validation)

Decision support:
- **Advisory maintenance** measures
- Maintenance **scheduling optimization**
- Information **sharing and visualization**

Table of contents

The research allows to deduce aspects to be implemented in a predictive maintenance concept. The realization still has unfulfilled requirements

PERSPECTIVES & PREREQUISITES
FOR LIB CELL MANUFACTURING

- → Being able to consider complex process related interdependencies
- → Decreasing risks in handling hazardous material
- → Reducing costs through scrap rate reduction
- → Need for ICT infrastructures with sensing technology for processing big data
- → Traceability over production chain
- → Expert domain knowledge for equipment modelling

KEY TAKE AWAYS OF THE PROPOSED CONCEPT

The proposed concept comprises a holistic process of production process analysis, data acquisition, data preprocessing, health indicator construction and fault diagnostics, RUL prediction, failure indicator analysis, and maintenance schedule optimization. For accurate machine fault diagnostics and further estimations on RUL, a production process must be proven in robustness to guarantee the extraction of high-quality data. This implies an intense examination and analysis of process characteristics to finally observe the proper parameters and to install the right sensorial measurement systems. Inline, online and environmental data acquisition is of importance to trace anomalous machine and process characteristics. In addition, high attention shall be given to health indicator construction to empower proposed diagnostic techniques. Industrial Internet of Things (IIOT) support the aggregation of needed production information. The Data Mining approach enables to use the collected information. With the proper Data Mining techniques, the relevant content can be extracted under the premise of utilizing historical and real-time data. The main benefits in combining component simulations with deep learning prognostics are fault tolerance, adaptability, higher failure transparency and cost-effective model development. Nevertheless, limitations emerge through still existing lack in model explanation, which designates difficult determination of failure influences.

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List of References

ATAMURADOV, V., K. MEDJAHER, P. DERSIN, B. LAMOUREUX und N. ZERHOUNI. Prognostics and Health Management for Maintenance Practitioners - Review, Implementation and Tools Evaluation [online]. International Journal of Prognostics and Health Management, 2020, 8(3). ISSN 2153-2648. Available under: doi:10.36001/ijphm.2017.v8i3.2667

SAI, V.C., M.V. SHCHERBAKOV und V.P. TRAN. Data-Driven Framework for Predictive Maintenance in Industry 4.0 Concept. In: A.G. KRAVETS, P.P. GROUMPOS, M. SHCHERBAKOV und M. KULTSOVA, Hg. Creativity in Intelligent Technologies and Data Science. Cham: Springer International Publishing, 2019, S. 344-358. ISBN 978-3-030-29742-8

SHIN, I., J. LEE, J.Y. LEE, K. JUNG, D. KWON, B.D. YOUN, H.S. JANG und J.-H. CHOI. A Framework for Prognostics and Health Management Applications toward Smart Manufacturing Systems [online]. International Journal of Precision Engineering and Manufacturing-Green Technology, 2018, 5(4), S. 535-554. ISSN 2288-6206. Available under: doi:10.1007/s40684-018-0055-0

SOLLE, D., B. HITZMANN, C. HERWIG, M. PEREIRA REMELHE, S. ULONSKA, L. WUERTH, A. PRATA und T. STECKENREITER. Between the Poles of Data-Driven and Mechanistic Modeling for Process Operation [online]. Chemie Ingenieur Technik, 2017, 89(5), S. 542-561. ISSN 0009286X. Available under: doi:10.1002/cite.201600175

SONG, L., L. WANG, J. WU, J. LIANG und Z. LIU. Integrating Physics and Data Driven Cyber-Physical System for Condition Monitoring of Critical Transmission Components in Smart Production Line [online]. Applied Sciences, 2021, 11(19), S. 8967. Available under: doi:10.3390/app11198967

TRAINI, E., G. BRUNO, G. D'ANTONIO und F. LOMBARDI. Machine Learning Framework for Predictive Maintenance in Milling [online]. IFAC-PapersOnLine, 2019, 52(13), S. 177-182. ISSN 24058963. Available under: doi:10.1016/j.ifacol.2019.11.172

Zhang, Huiguo; Kang, Rui; Pecht, Michael. A hybrid prognostics and health management approach for condition-based maintenance, 2009 IEEE International Conference 2009, 1165–1169, 10.1109/IEEM.2009.5372976

ZHANG, W., D. YANG und H. WANG. Data-Driven Methods for Predictive Maintenance of Industrial Equipment: A Survey [online]. IEEE Systems Journal, 2019, 13(3), S. 2213-2227. ISSN 1932-8184. Available under: doi:10.1109/JSYST.2019.2905565