Improving Continuous Dry-Coating of LFP Cathodes through Quality Assurance and Process Monitoring with AI

Philipp Heugel[1], Frank Sehnke[2], Ingo Bardenhagen[3], Christian Girsule[4], Nico Klar[2], Florian Hoffmann[4], Benjamin Schumm[4], Franziska Klein[1], Jens Tübke[1]

1 Fraunhofer Institute for Chemical Technology ICT, Joseph-von-Fraunhofer-Straße 7, 76327 Pfinztal, Germany
2 Center for Solar Energy and Hydrogen Research Baden-Württemberg (ZSW), Simulation and Optimization (SimOpt), Meitnerstraße 1, 70563 Stuttgart, Germany
3 Fraunhofer Institute for Manufacturing Technology and Advanced Materials IFAM, Wiener Straße 12, 28359 Bremen, Germany
4 Fraunhofer Institute for Material and Beam Technology IWS, Winterbergstraße 28, 01277 Dresden, Germany

MOTIVATION

- Dry coating of Li-ion electrodes can eliminate toxic solvents and energy-intensive drying, enabling greener and cheaper manufacturing and therefore cells. [1]
- Industrial implementation is limited by tight process windows (mixing, fibrillation, calendering) and lack of robust inline quality control. [2]
- ➢ **Development of an AI- and data-driven framework for continuous dry coating** of LFP cathodes (DRYtraec®) that links process and sensor data with electrochemical performance

EXPERIMENTAL

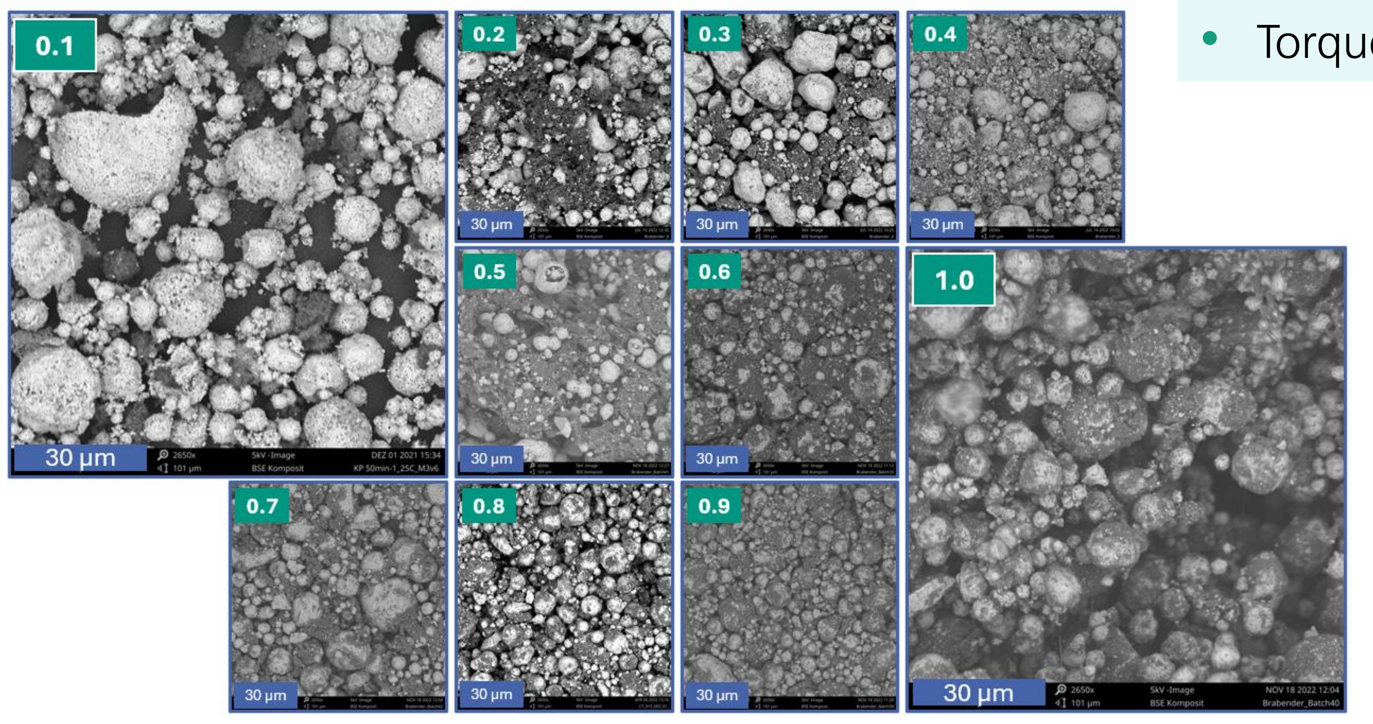
Dry process chain

- Dry mixing & kneading of LFP / SuperC65 / PTFE (90/8/2 wt%) in batch mixer or twin-screw extruder
- Continuous dry transfer coating with DRYtraec® onto Al current collector

DATA ACQUISITION & STORAGE

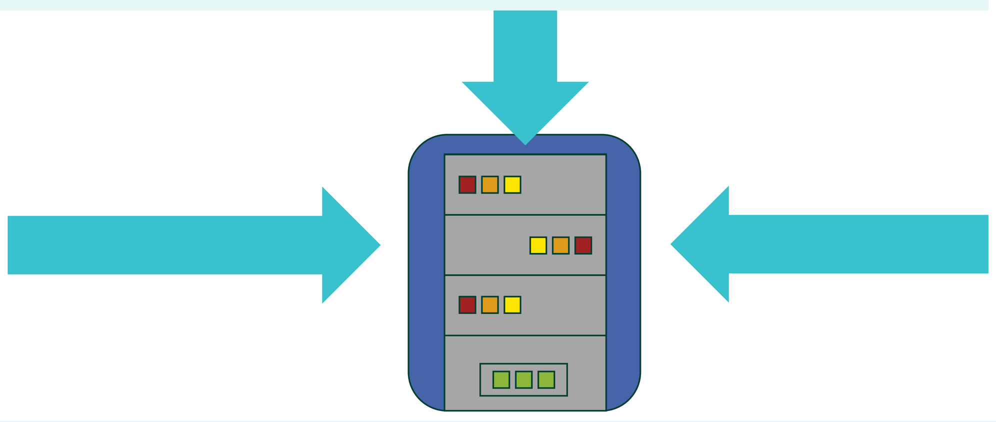
Dry mixing & kneading

- SEM investigation to evaluate quality of dry mixing



Sensor integration (inline monitoring)

- Gap & roll pressure sensors and laser triangulation for coating thickness, compaction and roughness
- Torque and roll speed for shear and PTFE fibrillation

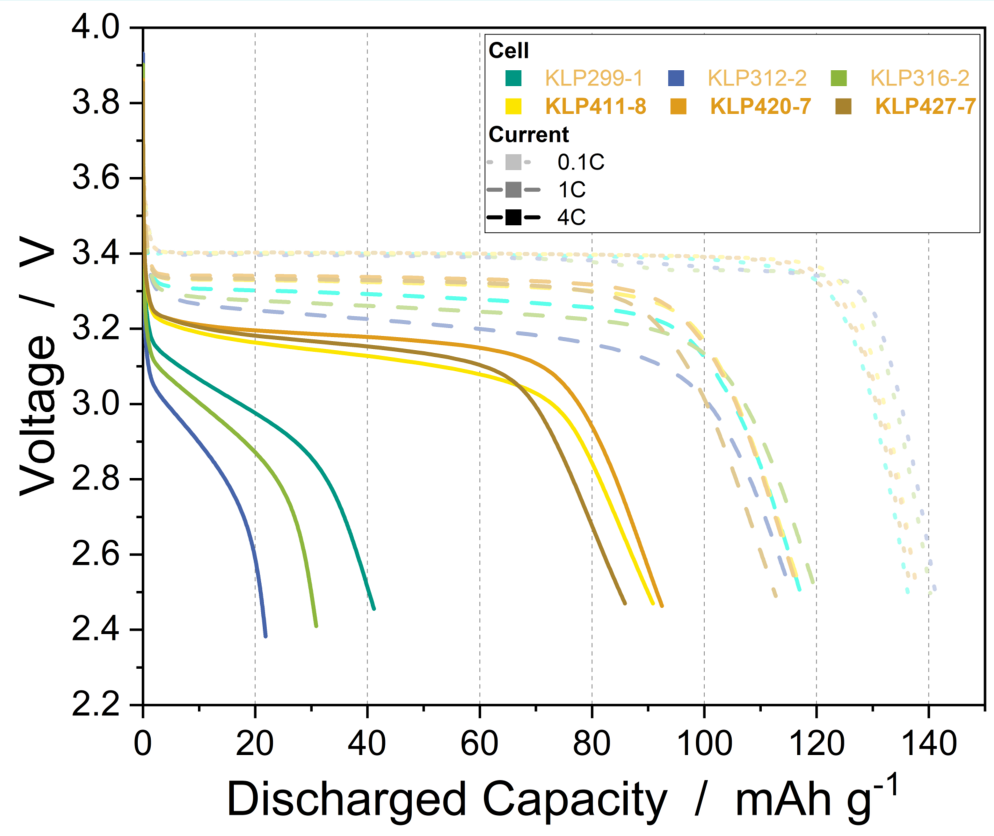


Database and infrastructure

Unified centralized database combining process parameters (mixing, extrusion, DRYtraec®), inline sensor streams, offline characterization and electrochemical performance

Electrochemical data

- Cycling with different C-rates as quality gate and performance indicator



DATA PROCESSING

DNN-based virtual sensors

- predict e.g. loading and density

DNNs & CNNs

- DNNs for regression, feature importance and virtual sensors [3]
- CNNs trained on SEM images to replace subjective quality scores (0–1) (~3 % nRMSE) [4]

Digital twin

- Hierarchical digital twin for the complete line
- <100 ms on standard CPU → real-time capable [5]

"Science Advisor"

- Active learning + Bayesian optimization
- ➢ Propose optimal machine settings under competing objectives (4C capacity vs. coatability) [6]

CONCLUSION

Process understanding

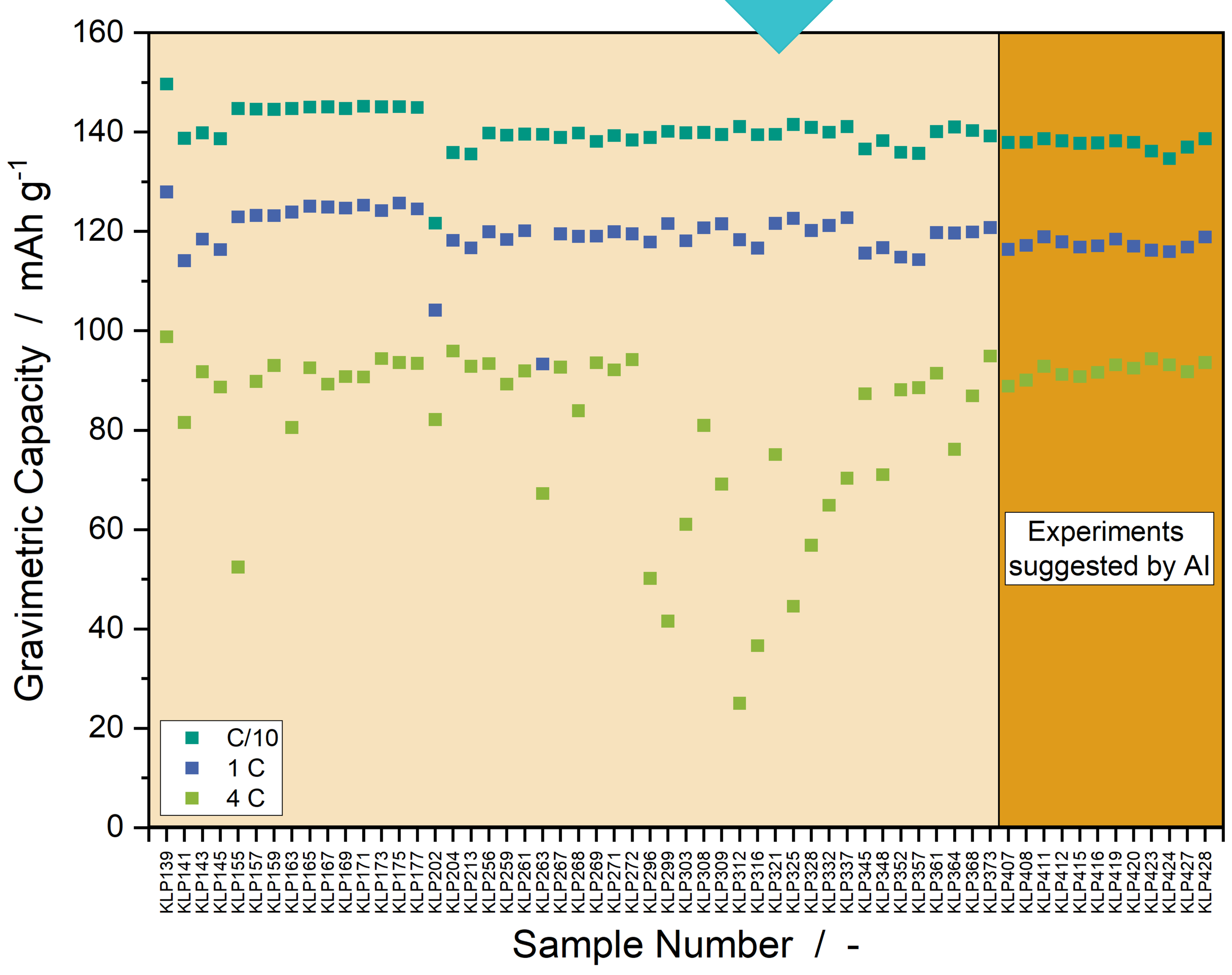
- CNN-based evaluation of SEM images correlates mixing/extrusion settings, shear input and PTFE fibrillation with granulate quality.
- Feature importance and symbolic regression identifiy gap, drive, kneading temperature and granulate quality as key levers for loading and density [7].

Predictive performance

- For LFP loading prediction, nRMSE ≈ 1.6–1.9 % with controllable parameters + virtual sensors.
- Virtual thickness sensor correlates with loading and is sufficient for fast inline estimation.

AI-guided coating optimization

- AI-proposed DRYtraec® settings are non-intuitive from empirical experience but enable largely defect-free coatings (coatability ≥ 0.8), deliver stable 4C capacities (≥ 90 mAh g^{-1}), while maintaining high 0.1C and 1C capacities.
- Bayesian multi-objective optimization finds a compromise between 4C capacity and coatability, with only minor sacrifices in each metric.



References

[1] B. Schumm, A. Dupuy, M. Lux, C. Girsule, S. Dörfler, F. Schmidt, M. Fiedler, M. Rosner, F. Hippauf and S. Kaskel, Advanced Energy Materials, 15(24) (2025).
[2] N.-Y. Kim, J.-H. Kim, H. Koo, J. Oh, J.-H. Pang, K.-D. Kang, S.-S. Chae, J. Lim, K. W. Nam and S.-Y. Lee, ACS Energy Lett., 9(11), 5688–5703 (2024).
[3] J. Schmidhuber, Neural networks : the official journal of the International Neural Network Society, 61, 85–117 (2015).
[4] LeCun, Yann and Bengio, Yoshua, Convolutional networks for images, speech, and time series, Cambridge, MA, USA, MIT Press (1998).
[5] Z. Song, C. M. Hackl, A. Anand, A. Thommessen, J. Petzschmann, O. Kamel, R. Braunbehrens, A. Kaifel, C. Roos and S. Hauptmann, Sustainability, 15(6), 5259 (2023).
[6] B. Shahriari, K. Swersky, Z. Wang, R. P. Adams and N. de Freitas, Proc. IEEE, 104(1), 148–175 (2016).
[7] Trevor Stephens, Genetic Programming in Python, with a scikit-learn inspired API (gplearn), https://github.com/trevorstephens/gplearn (2022).

The presented work was funded by the German Federal Ministry of Education and Research (BMBF) in the joint project KontElPro (03XP0325A.)

SPONSORED BY THE Federal Ministry of Education and Research