Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 106 (2022) 27–32

www.elsevier.com/locate/procedia

9th CIRP Conference on Assembly Technology and Systems

Development of a Digital Twin for Improved Ramp-Up Processes in the Context of Li-Ion-Battery-Cell-Stack-Formation

K. Husseini*, N. Schmidgruber, H. W. Weinmann, K. Maibaum, J. Ruhland, J. Fleischer

Institute of Production Science (wbk) of Karlsruhe Institute of Technology, Kaiserstraße 12, 76131 Karlsruhe, Germany

* Corresponding author. Tel.: +49 1523 9502664; *E-mail address:* kamal.husseini@kit.edu

Abstract

The ramp-up of machines for stack formation processes in the context of battery cell production is difficult due to a lack of knowledge about cause-effect relationships. This concerns the initial setup of the machine as well as the change of process input variables. For example, there are strong material dependencies in the area of cell stack formation of battery cells. Individual adjustments of the machine parameters to the different materials are therefore necessary. Digital twins represent the production process and the machine operations in a virtual environment. Cause-effect relationships can thus be quantified and evaluated. Optimization approaches for ramp-up-processes can be tested with low risk in virtual space before they are implemented in reality. This paper describes the development process of a digital twin representing a machine for flexible cell stack formation of pouch cells. As basis for the digital twin, a kinematic process model of the machine is developed from the underlying CAD files. Sensors and actuators are virtually integrated in the design environment of the machine. Connecting the model to a virtual controller, allows virtual testing and evaluating of the developed PLC code within the digital twin. Furthermore, the development of a simulation model for the prediction of the electrode web tension, as a quality-critical parameter, is presented. This purpose requires relevant aspects of the machine, for example the unwinder drive behaviour, to be recognized and integrated. In order to enable near-real-time runability, this simulation model is converted into a reduced-order-model. This substitution can be validated by tracing and comparing the web tension during commissioning scenarios on the real machine. Therefore it is possible to virtually represent control-side kinematic processes while also making statements regarding the web tension of the electrode material. The resulting functional digital twin of the flexible stack formation machine will be used to optimize the process parameters as well as the current machine design.

Keywords: Battery Cell Manufacturing, Digital Twin, Stack Formation

1. Introduction

Due to the increasing demand for lithium-ion battery cells, efficient production processes and machines will be necessary to meet the requirements of the market [1]. The cause-effect relationships occurring in the production processes have not been finally understood yet, which makes the commissioning and ramp-up of the production machines more difficult and results in material scrap and high production costs [2].

As a part of the development trend "Industry 4.0" and the digitalization, the use of digital twins for production processes of any kind is becoming increasingly important [3]. These are used to represent real physical objects or processes in virtual space and allow parameter correlations to be explored [4]. First developments and applications of digital twins have already taken place in the context of lithium and post-lithium battery cells and their production processes, which will be described further on.

In [5–7] methods and approaches are described for the development of digital twins, which describe the physical and electrochemical behavior of the battery cell or battery system. In [8] the influence of calendering on cell performance is

10.1016/j.procir.2022.02.150

investigated using a digital twin. The use of a cloud-based digital twin to describe battery behavior in electric vehicles is presented in [9].

Overall, it can be seen that the use of digital twins relates predominantly to the battery cell itself, or the overarching production system. The development of digital twins for the respective production machines has only taken place to a limited extend to date. In this paper, a digital twin of a production machine for cell stack formation is developed to optimize the ramp-up process. Specifically, the development of the digital twin is being done on the *Coil2Stack* machine, which has been developed at the *wbk – Institute of Production Science of KIT* and is described in [10, 11].

2. Development of the Digital Twin

In the following, the concept of the production machine and the process are shown and the methodology for the construction of the digital twin is presented. The machine concept is shown in Fig.1. The machine continuously processes incoming electrode material. The material is provided to the process as an electrode coil. The electrode web is guided by a roll-setup to a flexible and functionally integrated handling and singulation system. A material storage unit is integrated to ensure a constant feed rate. In order to control the web run, a web-edge control system is integrated. A web-tension measuring roller is built in to capture the web-tension shortly before the material is fed to the flexible handling system. The web tension is controlled by the unwinder and the material storage system at this point. The handling system is able to grip the electrode material with the help of three large area surface vacuum grippers and produce electrode sheets by using a shear cut. The singulated electrode-sheets are then placed on a table. The distance between the vacuum grippers can be adjusted automatically. This allows different sheet lengths to be set which are going to be singulated out of the incoming electrode web. The handling system then places the cut electrode sheets on the stacking table at a constant depositing speed.

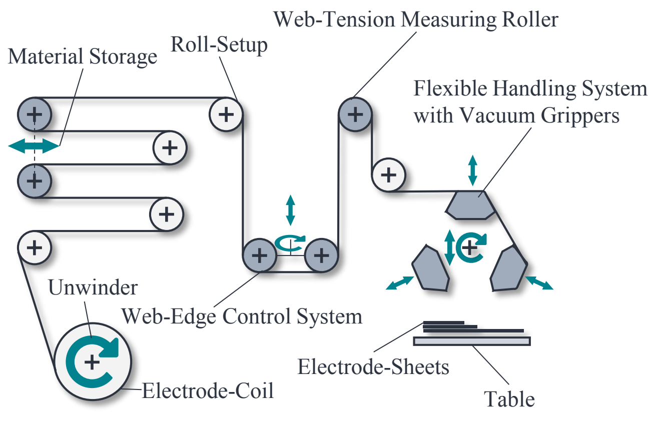

Fig. 1. Machine Concept

The web tension of the electrode material is a critical parameter for determining whether the material can be processed in the system or not. If the web tension on the handling element is too low the shear cut cannot be performed and the electrode web cannot be guided in the system. If the web tension is too high, the electrode sheet may "rip off" during the cutting process and the vacuum grippers are not able to hold the electrode web in place. Furthermore, it can be seen that the web tension has an influence on the dimensional accuracy of the electrode sheets. The entire system is characterised by a complex motion sequence of the handling system, the adjustable drive behavior on the control-system side and the resulting material behavior in the production machine. The interdependencies between the motion sequence, the occurring web tension, the general machine/system parameters and the material behavior are largely unknown. This problem complicates both, the initial commissioning and the testing of the generated control code, as well as the commissioning of the system in the event of a change of material or change of the sheet lengths of the electrodes to be produced. Long commissioning times and the generation of material scrap are the result. This leads inevitably to an increase in costs. Against the background of the previous process steps, the material is associated with a high cost and energy expenditure. Material scrap is therefore a major cost driver.

The transfer of the production machine and the process into a digital twin enables the testing of the commissioning scenarios mentioned above with no risk in virtual space. Based on this digital twin, optimization approaches can be derived and implemented in reality. The entire structure of the digital twin is shown in Fig.2. The digital twin is made up of three parts. These are the kinematic process model, the web tension simulation model and a virtual control unit. The kinematic process model represents the system in the corresponding CAD model. Virtual sensors and actuators are additionally integrated here to visualize the movement sequence of the system. In the web tension simulation model, mechanical components, the control structure of the machine and the drive behavior of the system are simulated in order to be able to make conclusions about the web tension behavior. The third component of the digital twin is the virtual control unit.

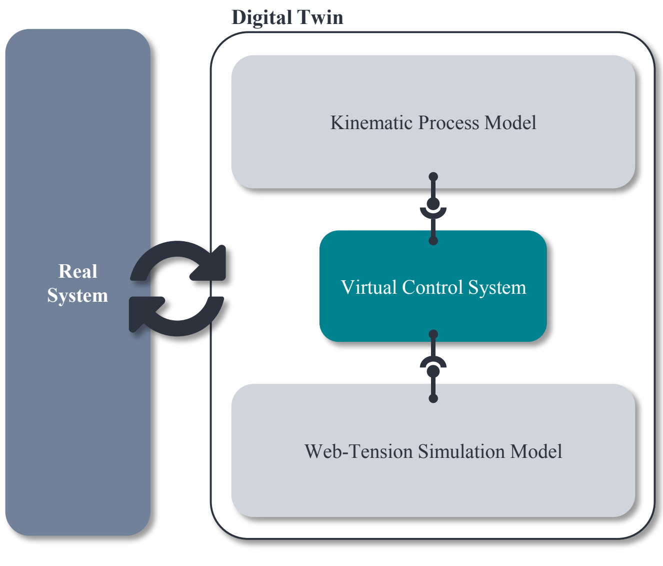

Fig. 2. Structure of the Digital Twin

The virtual controller projects the corresponding signals of the control code to the respective components in the models. In this way, the system behavior in the model can imitate that of reality. The software used to build up the digital twin is *NX-Mechatronics Concept Designer / SIMIT (kinematic process model), Simcenter AMESIM (web tension simulation model) and PLC-SIM-Advanced (virtual control system) from SIEMENS AG.* An information or data exchange between the digital twin and the real system marks the connection between the real and virtual system. For example, the actually measured behavior of the drives can be fed into the models of the digital twin in order to determine the web tension at any position. The other way around, there is the possibility of determining optimization approaches based on the digital twin and returning optimized control parameters to the real system. However, in the following chapters, the development process of the kinematic process model and the web tension simulation model is described.

2.1. Kinematic Process Model

The kinematic representation of the real system is based on the solid bodies prepared in the CAD-Modell of the production machine. The mechanical relations between the solid parts are defined by constraints. To implement kinematic actions between the parts, corresponding constraints are converted into movement axis. These movement axis are subsequently used as virtual representations of the actuators of the production machine. By defining kinematic variables as feedback, interactions between the process model and e.g. the PLC *(programmable logical controller)*-simulation are made possible. For optimal use, the model input and output get connected to a behavior model. The behavior model offers the virtual mechatronic components the framework to interact with a logical controller, in this case a virtual representation of the PLC.

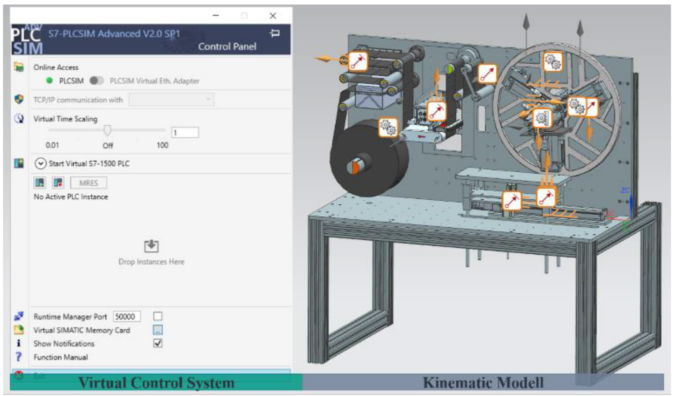

Fig. 3. Implemented Kinematic Process Model

Fig. 3 depicts the key parts of the kinematic process model. The virtual control system implements the PLC-program and offers it the virtual Input and Output-signals. Output signals trigger the virtual actuators of the kinematic model. Within the model, virtual sensors return the position signals of the machine parts to the virtual controller. These signals are transmitted through the virtual Profinet-connection provided by the behavior model and then processed in the inner logic of the virtual control system. This makes it possible to virtually represent and optimize the kinematic sequences of the machine. These sequences are finally considered in the web tension simulation model.

2.2. Model for Determining the Electrode Web Tension

In the following, the development process of the web tension simulation model is presented. In the model, relevant components and functions of the production machine are modelled in order to be able to simulate the web tension of the material. Fig. 4 shows the structure of the simulation model.

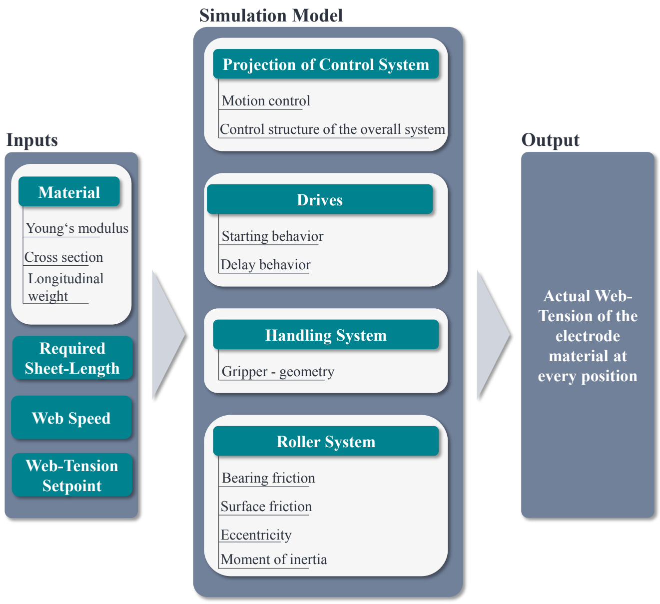

Fig. 4. Structure of the Web-Tension Simulation Model

The input, the aspects considered in the model itself and the output is illustrated. The input consists of properties of the electrode material. These are the young's modulus, the cross-sectional area of the electrode web and the longitudinal weight of the electrode material. Other input parameters are the required sheet length, the web speed of the electrode material as well as the setpoint for web tension. These variables are then processed in the simulation model. In the simulation model itself, the entire control architecture is modelled and the PLC-generated motion sequences are used to control the drive models. Furthermore, drive models are created in which the start-up and delay behavior is considered. The entire roller system of the production machine is represented. Here, mainly the aspects of bearing friction, friction between sheet and roller and the inertial behavior are considered. Furthermore, the geometry of the gripper as a part of the handling system is considered. The handling system is modelled as a non-circular roller element. The different aspects of the simulation model are based on time-dependent differential equations. In the simulation model, these differential equations, which describe the physical effects of the different machine parts, have to be solved numerically. This is associated with a high computational processing effort. Finally, this model is comparatively transformed into a reduced order model. Here, a data-based connection is set between the input and output parameters. This should minimize the processing time and thus enable near-real-time runability. The reduced order model is generated by an artificial neural network. This consists of three hidden layers with ten cells each. The activation function is *tangens hyperbolicus.*

Experimental Setup

The models are validated by tests on the real machine. Fig. 5 shows the experimental setup. Here, calendered anode material is processed and the web tension is measured.

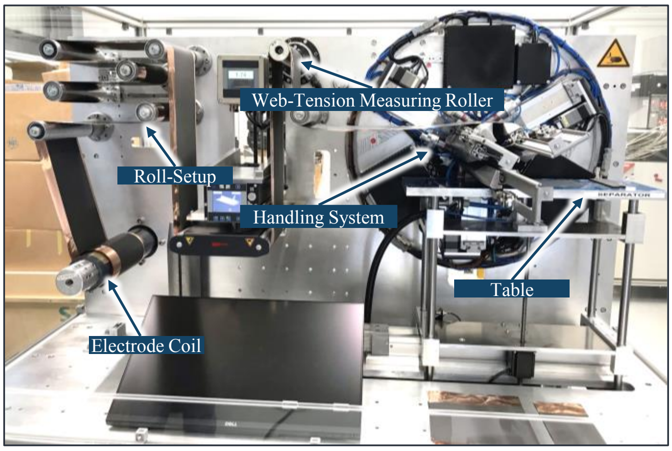

Fig. 5. Experimental Setup at the Coil2Stack Demonstrator

For the experiments, different sheet lengths and web speeds are selected. Three experimental setups were created in which the machine parameters were varied stepwise. The variation of the parameter values is oriented on a production scenario with the requirement of a specific output of electrode-sheets per second. The longer the required sheet length, the higher the web speed to be set. In order to enable controlled web guiding at increasing web speeds, the setpoint of the web tension was also increased with each step. Regarding the material parameters, the young's modulus of copper has been used for the simulation. The other values were determined on an experimental basis. Table 1 shows the considered input parameters.

Table 1. Input Parameters

	Material Parameters			Machine Parameters		
No.	Yong's Modulus	Cross Section	Long. Weight	Req. Sheet Length	Web Speed	Web Tension Setpoint
1	100 GPa	16.46 mm²	358.85 g/m	160 mm	8 mm/s	8 N
2	100 GPa	16.46 mm²	358.85 g/m	210 mm	10 mm/s	10 N
3	100 GPa	16.46 mm²	358.85 g/m	260 mm	12 mm/s	12 N

3. Results

In this chapter, the results of the usage of the digital twin and the described experiments are shown and evaluated. First of all, the measured data sets of the web tension are compared to the simulated ones. From this, a conclusion about the quality of the web tension simulation model can be made. Then, the optimization of the processing time by the reduced order model is validated. For this purpose, the deviation of the reduced order model from the original simulation model is quantified. In order to determine the deviation, the Root Mean Square Error (RMSE) is used as a characteristic value. The calculation is based on the following equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(F_i - \hat{F}_i)^2} \quad (1)$$

For the validation of the simulation model F_i describes the measured data points of the web tension while $\hat{F}_i$ describes the simulated data points. For the validation of the reduced order model and the simulation model, the factor F_i describes the data points of the simulation model and $\hat{F}_i$ describes the generated data points with the reduced order model. The Factor n represents the number of data points.

In the following, the comparison of the simulation model with the measured data is shown. The raw data sets of the measurements were additionally processed and filtered. This is intended to fade out disturbances and to reveal and visualize characteristics and typical variations of the measured web tension over machine-operation-time in the different experimental setups. The *Savatzky-Golay-smoothing-filter* was used for this purpose. The results of the first setup (Table 1-No. 1) are shown in Fig.6. The RMSE-value of the simulation model, compared to the unfiltered data set is 0.944 N. In comparison to the filtered data set, the value is 1.012 N.

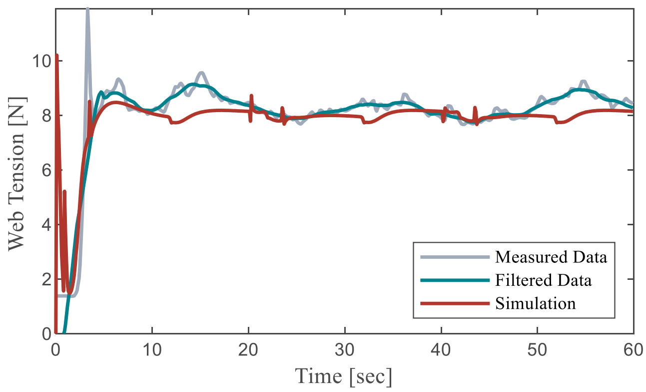

Fig. 6. Results: Setup No. 1

The results of the second setup (Table 1-No. 2) are shown in Fig. 7.

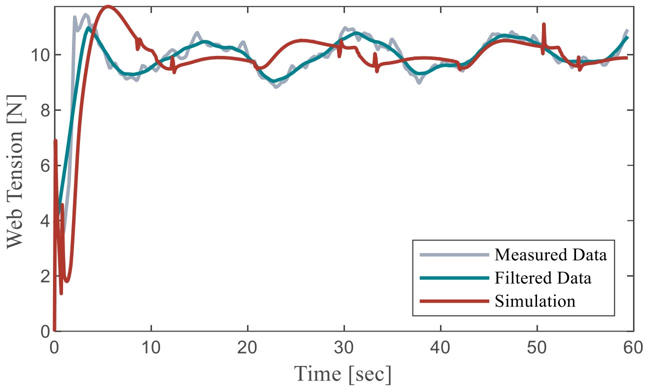

Fig. 7. Results: Setup No. 2

Here the RMSE of the simulation, compared to the unfiltered data is 1.179 N. The RMSE of the simulation, compared to the filtered data is 1.098 N.

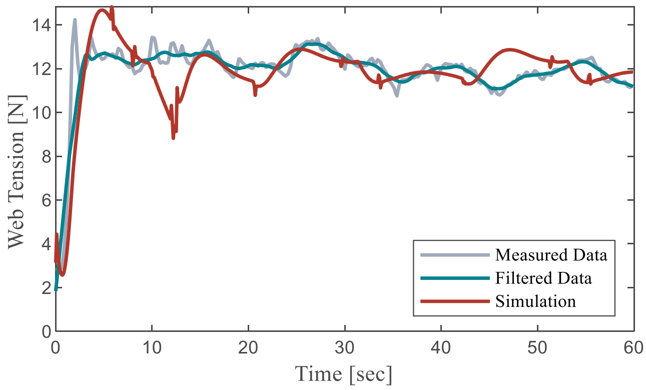

Fig. 8. Results: Setup No. 3

The results of the third setup (Table 1-No. 3) are shown in Fig.8. The RMSE of the simulation, compared to the unfiltered data set is 1.252 N. The RMSE, compared to the filtered Data is 1.078 N. Overall, the measured data sets show that the web tension setpoint cannot be completely achieved by the machine in the considered period. The reason for this is primarily the complex motion sequence of the handling element and the delay behavior of the whole control system. The simulation model also represents this behavior. However, deviations from reality can be noted. The deviations in the start-up phases can be explained by the manual set-up process of the machine. Here, the material is manually fixed to the handling system, which results in an uncontrolled measured web tension in the start-up phase. In the simulation model, it is primarily the start-up behavior of the drives that leads to a characteristic web tension variation in the start up phase. The effect of manual fixation is not considered in the simulation model. The results of the conversion of the simulation model into the reduced order model are shown below. The reduced order model is an artificial neural network that has been generated using simulated data.

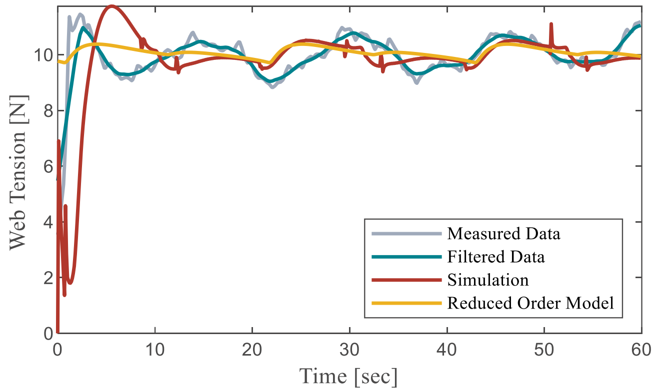

Fig. 9. Results: Reduced Order Model Setup No. 2

The comparison of the reduced order model with the simulated and measured data is shown in Fig. 9. Here the data of the web tension with the second setup is shown exemplarily. The simulation was carried out for 60 seconds of machine operation with a time step of 0.05 seconds. Thus, 1200 data points were simulated. The original simulation model takes total of 33.69 seconds to provide this data. This results in a computing speed of 35.6 data-points per second. In comparison, the reduced order model generates the same amount of data within 0.0067 seconds. This leads to a computing speed of 180,000 data-points per seconds. Thus, the computing speed has been increased by $5.06 \cdot 10^5$ %. This enables near-real-time runability. Furthermore, a deviation between the reduced order model and the simulation can be noted. Here the RMSE value is 1.470 N.

4. Conclusion

The occurring cause-effect relationships in battery cell production are not yet sufficiently understood. For this reason, the commissioning of machines and plants is difficult. Material scrap and increased production costs are the result. Digital twins enable processes to be mapped virtually. This allows a ramp-up of the plant to be done virtually and with low risk. Optimization approaches can be derived from this and implemented in reality. This paper presents the development process for a digital twin of a continuously working and flexible cell stacking machine. For this purpose, a kinematic process model was first developed, which visualizes the motion sequences of the system. These sequences can thus be verified in virtual space. Furthermore, a simulation model was developed to predict the occurring web tension. For this purpose, relevant machine components and the material behavior were modeled. The simulation model was validated by a series of tests. Here, the simulated web tension was compared with measured data. Compared to the raw measurement data a minimum RMSE of 0.944 N for the first experimental Setup and a maximum RMSE of 1.252 N for the third experimental Setup were determined. In order to minimize the computing time and enable near real-time runability, the simulation model was converted into a data-based reduced order model. For this, an artificial neuronal network was used. The computing speed could thus be increased by $5.06 \cdot 10^5$%. The reduced order model has been compared to the simulation model. Here a RMSE value of 1.470 N has been noted. The accuracy of the simulation model to the measured values and the accuracy of the reduced order model to the simulation model is sufficiently. Larger web tension fluctuations can be modeled and setting parameters can be checked virtually. The cycle time of the control system is 2 milliseconds. To ensure a coupling of the reduced order model with the control system the model must provide at least one data point per cycle. The model supplies 360 data points per cycle. Using a higher model for the reduced order model would increase the accuracy to the simulation model as well as computation time. More detailed investigations are to be carried out. A virtual controller controls the kinematic process model as well as the simulation model for the web tension. This makes it possible to carry out various commissioning scenarios in virtual space. Statements regarding the quality-critical web tension and kinematic process limits can be made and optimal parameters can be derived virtually.

5. Outlook

The outlook of this work includes first the detailed further development of the simulation model. All components and functional elements of the production machine are to be extensively modelled and digitized. This includes for example the consideration of other mechanical components, such as the ball screws, deformation effects in the handling system and the vacuum gripper suction effects. In addition, the material behavior is to be worked out in more detail. Wrinkles and damage effects are in the focus. Finally, a concrete conclusion on the quality of the intermediate product is to be made on the basis of the simulated web tension. This includes the dimensional accuracy of the cut electrode sheets and the deposition accuracy of the machine. Furthermore, a database is to be developed with the help of the simulation model. With this database an AI model is to be systematically developed. This AI model is able to predict any commissioning scenario fast and precisely. This method is intended to provide a practical way of optimizing the ramp-up of new production processes. This will generate an information and data base, which does not exist due to the limited production experience. Extending this model with real measured data enables a continuous optimization approach regarding prediction accuracy. Another overarching outlook represents the transfer of this method to the other processes of battery cell manufacturing. Process-wide optimization approaches can then be determined and tested virtually.

Acknowledgements

The presented research is funded by the *German Federal Ministry of Education and Research* under the funding codes 03XP0252B (Project: *E-Qual*) and 03XP0324C (Project: *ViPro*), the *Center for Electrochemical Energy Storage Ulm | Karlsruhe (CELEST)* and the *Battery Technology Center of KIT*.

References

[1] S. Michaelis et al., Roadmap Batterie-Produktionsmittel 2030: Update 2020. Frankfurt am Main: VDMA Verlag GmbH.

[2] J. Schnell et al., “Data mining in lithium-ion battery cell production,” Journal of Power Sources, vol. 413, pp. 360–366, 2019, doi: 10.1016/j.jpowsour.2018.12.062.

[3] Pires, F.; Cachada, A.; Barbosa, J.; Moreira, A. P.; Leitão, P. (Ed.) (2019): Digital Twin in Industry 4.0: Technologies, Applications and Challenges. IEEE 17th International Conference on Industrial Informatics (INDIN). Helsinki, Finland, 22/07/2019-25/07/2019. Research Centre in Digitalization and Intelligent Robotics (CeDRI).

[4] D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks, “Characterising the Digital Twin: A systematic literature review,” CIRP Journal of Manufacturing Science and Technology, vol. 29, pp. 36–52, 2020, doi: 10.1016/j.cirpj.2020.02.002.

[5] J. Park et al., “Digital Twin‐Driven All‐Solid‐State Battery: Unraveling the Physical and Electrochemical Behaviors,” Adv. Energy Mater., vol. 10, no. 35, p. 2001563, 2020, doi: 10.1002/aenm.202001563.

[6] A. Sancarlos, M. Cameron, A. Abel, E. Cueto, J.-L. Duval, and F. Chinesta, “From ROM of Electrochemistry to AI-Based Battery Digital and Hybrid Twin,” Arch Computat Methods Eng, vol. 28, no. 3, pp. 979–1015, 2021, doi: 10.1007/s11831-020-09404-6.

[7] W. Li, M. Rentemeister, J. Badeda, D. Jöst, D. Schulte, and D. U. Sauer, “Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation,” Journal of Energy Storage, vol. 30, 1–2, p. 101557, 2020, doi: 10.1016/j.est.2020.101557.

[8] A. C. Ngandjong et al., “Investigating electrode calendering and its impact on electrochemical performance by means of a new discrete element method model: Towards a digital twin of Li-Ion battery manufacturing,” Journal of Power Sources, vol. 485, no. 1, p. 229320, 2021, doi: 10.1016/j.jpowsour.2020.229320.

[9] L. Merkle, M. Pöthig, and F. Schmid, “Estimate e-Golf Battery State Using Diagnostic Data and a Digital Twin,” Batteries, vol. 7, no. 1, p. 15, 2021, doi: 10.3390/batteries7010015.

[10] H. W. Weinmann, M. Eichelkraut, L. Wolke da Silva, and J. Fleischer, “Batteriezellenfertigung vom Coil zum Stack: Integriert, automatisiert und dadurch hoch flexibel,” C2 Coating & Converting, no. 4, pp. 21–24, 2020.

[11] H. W. Weinmann; H. Töpper, & J. Fleischer (2020), „Coil2Stack: Ein innovatives Verfahren zur formatflexiblen Batteriezellherstellung“, ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb, Band 115, Nr. 4, S. 241-243.