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Simulation-based assessment of the energy demand in battery cell manufacturing

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Abstract

Electric vehicles are seen as a solution towards mitigating the environmental impacts of the transportation sector as they do not produce tailpipe emissions. However, this technological shift in the transportation sector brings new environmental challenges. Particularly, the production of the battery system has been estimated to potentially contribute to around 50% of the total cradle to gate environmental impact of the production of an electric vehicle. In this regard, the energy required for the manufacturing of battery cells has been identified as one of the largest environmental and economic hotspots. While the emerging battery manufacturing industry is still highly unconstrained, the variability of product and processing parameters is difficult to capture and compare. Even more, battery cell manufacturing consists of a complex and dynamic combination of numerous continuous and discrete processes as well as technical building services which account for a high share on energy demand. This has led to a large uncertainty in the values reported in the current literature and also hinders the derivation of improvement measures. Against this background, the paper presents a simulation-based assessment of the energy demand in battery cell manufacturing. Based on collected field data, a multi-paradigm simulation of the battery manufacturing process chain has been built. Multiple simulations scenarios were subsequently run allowing to analyze the factors and circumstances driving energy demand. This paper aims to contribute towards enhancing the knowledge on the energy related impacts of traction battery systems and to provide a frame of reference for the variability of the required manufacturing energy that might be used as input for further sensitivity analysis in system assessment methodologies such as Life Cycle Assessment (LCA) or Life Cycle Costing (LCC) respectively Total Cost of Ownership (TCO).

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Keywords: Modelling, Energy, Sustainable development

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1. Introduction

The significance of the energy demand of industrial factories in developed countries will grow more and more in the future due to increasing energy prices and importance of renewable energies for sustainable production of products [1–3]. Batteries are a key technology for electromobility and energy costs make up an important share of overall cost in production. Minimizing energy costs would increase competitiveness of electric vehicles compared to conventional combustion vehicles. The raw material costs of batteries will represent around 75% of total costs by 2020. 17.4% of the remaining 25% non-material related costs are required for energy during the production process and consequently represents potential for further reducing battery costs [4]. Cell manufacturing processes and process chains are still unconstrained thus leading to high variability and uncertainty when assessing the energy requirements. In order to evaluate the effect of different production scenarios on the specific energy demand, modeling and simulation present an effective approach allowing to consider alternatives for energy reduction. Against this background, the present work introduces a methodology that enables assessing the energy demand for products in complex process chains. The simulation will be applied on the pilot plant production line of Battery LabFactory Braunschweig (BLB).

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2. Background

2.1. Battery cell manufacturing process chain

Battery production is characterized by a complex process chain with diverging and converging material streams. It can be divided into electrode production, cell assembly and cell finishing [5]. Fig. 1(d) shows different processes of the battery process chain (implemented at BLB). Batch, continuous and discrete processes have to be distinguished since the energy consumption patterns differ for each process type, causing large variations in the energy consumption over time in a dynamic production system. The electrode production consists of a dry and a wet mixing process, in which the slurry is prepared. The slurry is coated onto current collector foils and dried subsequently before it enters the calendering process. During cell assembly, the electrodes enter the dry room, where they are cut into single sheets, e.g. using laser cutting. The sheets are either stacked or winded (packaging) and contacted using ultrasonic welding. After a consecutive final drying process, the cells are housed in a hardcase or pouch foil and filled with electrolyte. Eventually, after a tempering step, the cells enter the formation step within a climate-controlled chamber, where they also undergo a quality evaluation for several days [5–7]. In addition to the process machines, the technical building services (TBS) represent another group of machines which are responsible for maintaining the factory building and especially controlled conditions in the dry room [8].

2.2. Battery Cell Manufacturing Energy Demand

Production energy analyses of the battery production have been conducted by several studies, with reported specific energy demands ranging between 34.3 Wh to 106.2 Wh per cell energy storage capacity. The large variability between the values can be explained by the different products that differ in size and energy storage capacity (72 Wh – 136.4 Wh), production scale (10^5 – $5x10^6$ cells per year) and system boundaries [9–14]. Most studies consider the energy consumption of the entire production as a single variable due to their study scope. Only few studies analyzed the distribution of energy consumption within the production process. Pettinger and Dong present data from a large-scale production plant by SOVEMA, comparing water- and solvent-based processing [13]. Schünemann developed a calculation model which includes energy consumption for battery production [12]. Yuan and colleagues provide a detailed battery manufacturing energy analysis for a LiMnO pouch cell using industry data from a pilot plant by Johnson Control [14]. Results of selected studies are shown in Table 1. However, due to the scope of these studies, they are mainly static and do not consider the dynamic interdependencies of the different processes in the production. They are therefore not suitable for a dynamic assessment of the energy demand in cell production. Moreover, operation modes are unclear and state of machines provide sources of uncertainties. The reviewed studies assess different cell types and system boundaries. This leads to relatively large deviations between the results.

Table 1. Energy consumption of production processes from selected studies.

	[12]	[13]	[14]	
Cell Energy	136 Wh	72 Wh	125 Wh	
Prod. Volume	$5x10^6$	10^5	$1.5x10^6$	
Process[a]				**Average**
Mixing	0.15	2.64	0.88	2%
Coating/Drying	11.44	15.42	51.20	38%
Calendering	0.15	5.97	3.04	5%
Stacking	1.17	5.97	6.16	7%
Final drying	16.57	5.97	-	20%
Electrolyte fill.	0.88	1.53	4.72	3%
Formation	0.88	2.92	0.56	3%
Dry room	2.56	-	31.20	12%
Other processes[b]	0.51	5.56	8.48	7%
Sum	**34.31**	**45.98**	**106.24**	**100%**

All values in Wh per Wh cell energy storage capacity

[a] Processes have been grouped or renamed

[b] Processes with low contribution which differ for each study

2.3. Dynamic Energy Demand Simulation Approaches

The dynamic simulation of energy demands aims at a model-based description of the energy consumption over time. It can support tasks that require the analysis of different scenarios of system variants, such as the production planning, peak load planning and the identification of energy efficiency and flexibility potentials. In order to fully represent the dynamic energy flows in a manufacturing system, the simulation approach needs to include

- diverging and converging material streams,
- continuous and discrete processes and machines,
- single and batch processing,
- specific machine states,
- as well as models for the technical building services (TBS).

Four main manufacturing system simulation paradigms can be distinguished: Discrete Event Simulation (DE), Dynamic Systems (DS), System Dynamics (SD) and Agent-Based Simulation (AB) [15]. While all simulation paradigms are suitable for energy-oriented simulation in general, most approaches are based on DE and AB. Herrmann and colleagues introduced a concept for energy oriented simulation of manufacturing systems based on a generic model using DE [16]. Thiede applied this concept for determining energy efficiency potentials [1]. Seow and Rahimifard developed a modelling framework which determines the embodied product energy and applied it to different machining processes [17]. Schönemann uses an approach based on AB for the multiscale simulation of a battery production system [8]. While this approach describes the dynamics of the energy demand specifically for the battery cell production, it focuses on varying process parameters and does not provide analyses of different production scenarios and machine failures. Concluding from the literature, there are suitable and well-explored approaches on dynamic simulation of energy demand in manufacturing. However, these approaches have either not been applied to battery manufacturing or do not focus on different production scenarios. Moreover, existing literature provides high variability for energy demand in battery production due to uncertainty in state of machines and their operation modes. Hence, a simulation model is developed for the battery cell manufacturing system that includes validated models allowing to assess energy consumption dynamically.

3. Methodology

Based on [8] a hierarchical multi-paradigm simulation approach was developed in order to dynamically describe the energy demand in battery production. The individual simulation paradigms – AB, DE, DS - allow splitting the complex battery production into separate elements. The simulation approach combines the benefits of each paradigm and enables coping with the different levels of abstraction in the production system.

3.1. Agent-based

The AB simulation defines the broader environment in which different agents interact dynamically with each other based on their implemented logic. Two classes of agents are introduced. Generic product unit and machine agents are generated at simulation execution (Fig. 1a). Product units represent (intermediate) products while machine agents embody the individual machines of the battery production chain. Importing machine-related parameters (e.g. process name, x-y-location, process power) ex ante via an Excel spreadsheet allows customizing the machine agents. The machine agents are sequentially ordered according to the battery process chain (Fig. 1d). Product unit agents move along the process chain and thus depict the material flow of (intermediate) products. The product units do not represent a fixed intermediate product, but rather reflect the process-specific output quantity, i.e. slurry after dispersion or calendered electrode after calendering.

3.2. Discrete event

DE simulation is used to implement the necessary logic into the machine and product unit agents (Fig. 1b). The agents flow through discrete states, which are connected via transitions. Each state can trigger actions and variable changes. At initial product unit arrival, the machine ramps up and passes the individual machine states idle and processing. Subsequently, the machine remains in idle until the next product unit arrives or shutdown time is exceeded. The machine parameters guide the product units to the next process step. Based on the imported machine-related parameters at simulation execution, each machine is specified according to the characteristics of battery production processes. However, due to the heterogeneity of machines in battery production (e.g. batch, continuous, discrete or temperature related warm up/cooling down processes), the setup of machines needs to be adjusted individually in order to implement the necessary level of detail. The state chart of the product units implements the necessary behavior enabling product units to move along the process chain.

3.3. Dynamic systems

DS simulation is used to describe the dynamic power demand of battery production. It is based on mathematical models depicting the real power demand of the machines. The model approach assumes average power demands for each machine state which requires recorded machine data by either stationary or mobile energy meters. During the simulation, the power demand of a machine is tracked continuously based on the machine state. Typically, power curves in battery production can be distinguished between electrode production, cell manufacturing and TBS (Fig. 1c). The continuous processes in electrode production are roll-to-roll processes with long process times and steady power demands. Cell manufacturing is dominated by discrete processes with distinct peaks during processing. TBS machines run continuously in order to provide necessary atmosphere conditions. Integrating the power curves allows determining energy demand of each individual process step. Dividing the total energy demand of battery production (sum of all machines) by the number of batteries produced provides the energy demand per cell.

4. Use case

The developed methodology was applied exemplarily to analyze the battery production process installed at the BLB. The BLB is an open research infrastructure of Technische Universität Braunschweig and covers the complete battery process chain. However, some assumptions had to be made as BLB does not consistently produce batteries during normal operation because of its research character. Average machine state power and process times have been determined according to the BLB process chain (Fig. 1d). The produced cells consist of 15 compartments (one anode and one cathode each) with a cell energy storage of 33 Wh. Process times may differ from industry standard as these are not optimized with regard to throughput, e.g. final drying of battery cells is operated as batch and occurs overnight. Only electrical power demand was considered in the simulation. The average power for ramp up, idle and processing for each equipment were measured automated and processed using a SCADA system. Ramp up, idle and process times were determined based on power data and refined through interviews with process experts at the BLB. A base scenario and three different variation scenarios have been examined in order to show the dynamic effect of different process parameters and different boundary conditions on overall energy demand and power curve (Table 2). The simulation was performed using Anylogic. The variation scenarios focus on electrode production since it accounts for

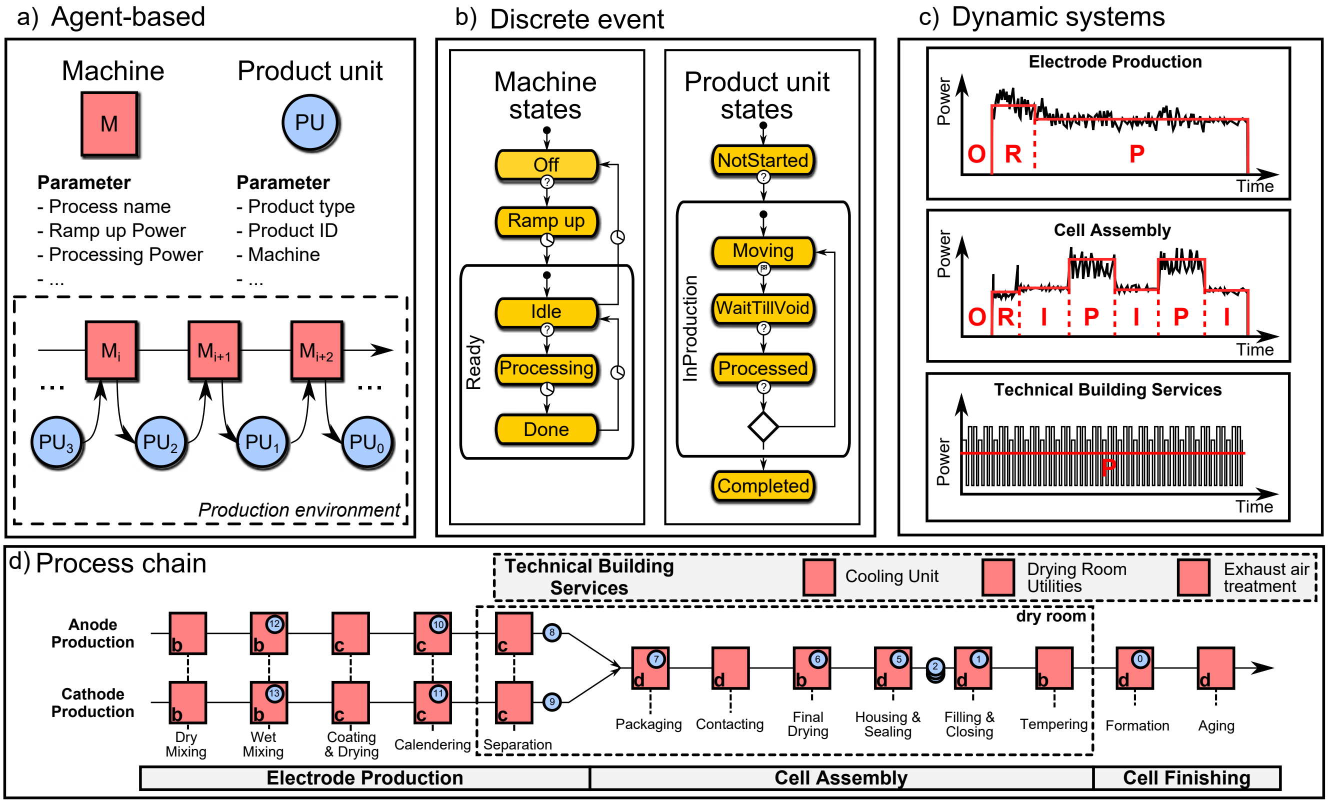

Fig. 1. Hierarchical multi-paradigm simulation. a) Machine and product unit agent representing the essential elements of the simulation. b) State charts for machines and product units implement logic of agents. c) Dynamic power demand of coating/drying (electrode production), z-folding (cell assembly) and cooling unit (technical building services) desribed by dynamic systems approach (O – Off, R – Ramp Up, I – Idle, P – Processing). d) Coupling of each simulation paradigm within the process chain simulation. Battery production process chain consisting of batch (b), continuous (c) and discrete (d) processes.

more than half of all process related energy (55%). Moreover, the energy demand of coating & drying and calendering varies due to warm up and cool down phases. The scenarios neglect the influence of TBS since it runs consistently at a given power demand and no negative effects on battery quality are assumed.

Table 2. Overview of different simulation scenarios.

Scenario	Description	Scope
Base	Base setup	EP + CA
1	New batch of material is triggered after four different starting points	EP
2	Scenario 1 + different process temperature in drying/calendering	EP
3	Scenario 1 + machine failures	EP

EP = electrode production; CA = cell assembly

4.1. Base case

The base case focuses on the electrode production, cell assembly and cell finishing. However, cell finishing clearly represents the bottleneck of the process chain due to the limited amount of connections (two temperature chambers with each 26 connections) and the long process time (ten days). This leads to a theoretical production volume for the BLB of approximately 1450 cells per year (280 working days). In order to assess the dynamic effects of the production process, we assumed unlimited access to charge/discharge connections. Consequently, we were able to simulate the production of 1000 battery cells in 25 batches of 40 cells each with an initial throughput time of 11.3 d. Each new batch started after dry mixing was finished. The average energy consumption per cell is 24.80 kWh, respectively 744.6 Wh/Wh. Production equipment is responsible for 295.9 Wh/Wh while TBS demands 448.7 Wh/Wh. The TBS needs to provide a constant dew point of -40 °C to -60 °C [5]. Consequently, energy requirement mainly consists of the cooling unit and the ventilation for the drying rooms. TBS energy demand needs to be allocated to cell production since it provides necessary atmospheric conditions inside the drying room. Table 3 shows the energy demand per process step for the base scenario.

Coating and drying represent the largest energy demand among the processing machines (133.6 Wh/Wh) due to high temperatures (up to 120 °C) in order to ensure complete evaporation of the NMP solvent. Cell assembly (17.2 Wh/Wh) requires less direct energy than electrode production (164.9 Wh/Wh) due to short process times and low average powers. The results of the simulation are in the same order of magnitude as [14] yet energy demand for TBS largely

Table 3. Energy consumption per process step with combined results for anodes and cathodes during electrode production for the base scenario.

Process step	**Energy demand per cell [kWh]**	**Energy demand per Wh [Wh/Wh]**
Dry mixing	0.01	0.3
Wet mixing	0.34	10.2
Coating & drying	4.45	133.6
Calendering	0.69	20.7
Seperation	0.004	0.1
Packaging	0.04	1.2
Contacting	0.002	0.1
Final drying	0.20	6.0
Deep drawing	0.01	0.3
Housing	0.01	0.3
Electrolyte filling & closing	0.29	8.7
Tempering	0.02	0.6
Formation	0.87	26.1
Aging	2.92	87.7
TBS	14.94	448.7
Total	24.80	744.6

exceeds due to research characteristics of BLB (long final drying process time and large dry room area). The simulation results agree with the measured results for the base scenario. While the processing energy demand remains constant, the ramp up and idle energy demand vary slightly throughout the simulation due to machine availability and temperature of coating & drying and calendering. In the following, three different scenarios have been examined in order to show the variability of energy demand per battery cell in battery production. These scenarios rely on the same assumption as the base scenario and neglect the influence of TBS since it runs consistently at a given power demand and assume no negative effects on battery quality.

4.2. Scenario 1: Different production start times

In scenario 1, production of new mixed material batches was triggered after dry mixing, wet mixing, coating/drying and calendering respectively leading to varying lead times and queues in electrode production processes. Since coating/drying and cathode calendering require heating up the machines, ramp up times strongly depend on previous machine temperature. Long idle times or stops between production lead to complete cool down and thus long ramp up and lead times. Consequently, different lead times as well as ramp up and idle energies affect overall energy demands and load curves during production. Energy for cell production and overall production time range between 164.6 Wh/Wh and 212.6 Wh/Wh (+29%), respectively 50.9 h and 137.8 h, without changing any process parameters. The results show lower energy demands for sooner starts of new batches caused by less energy losses for warming up the coater/dryer and calender (Table 4). Similarly, power curves differ significantly regarding length and shape generating different requirements on the electricity demand of a factory. Fig. 2 exemplarily shows power curves of individual process machines (top) and its accumulation (bottom) for start of new batch material after coating/drying clearly highlighting the influence of the coating/drying machine on overall power demand.

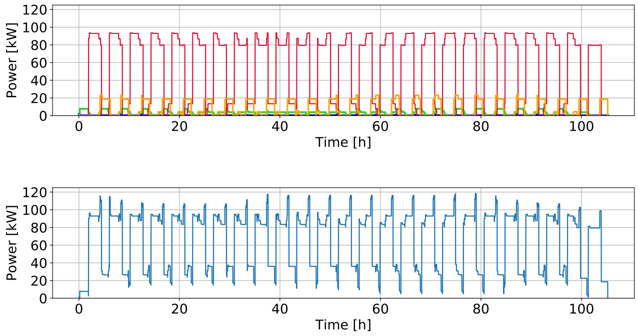

Fig. 2. Power curves for (top) process machines (red – coater/dryer, orange – calender, green – wet mixing, blue – dry mixer) and (bottom) accumulated processes.

4.3. Scenario 2: Varying process temperatures

Scenario 2 investigates in two sub-scenarios the effect of machine temperature on the energy demand considering the four different starting points from scenario 1. First, the calender temperature is reduced from 80°C to and 40°C (scenario 2.1). Lower temperatures require less ramp up times and a reduced power demand. High temperatures for cathode calendering are required to ensure adequate adhesion of active material on current collector yet may lead to unnecessarily high calender roll temperatures. Second, the simulation assumes the use of a water-based solvent instead of an organic solvent for cathode production (scenario 2.2). Water-based solvents are environmentally friendlier, less expensive and require lower temperatures (65°C compared to 120°C). Heating and cooling of the machines were modelled based on measured data for determination of ramp up time. Calendering cathodes at 40°C allows lowering energy demand from 18.3 Wh/Wh to 9.9 Wh/Wh per cell (-46%) thus reducing overall process machine energy demand by 5%. The use of water-based cathodes decreases the energy demand for coating/drying from 114.4 kWh to 19.2 kWh (-83%), respectively 58% for overall process machine energy demand thus presenting the largest potential for energy improvement regarding process machines.

4.4. Scenario 3: Consideration of limited machine availability

Scenario 3 examines the effect of probabilistic machine failures during electrode production via Monte Carlo simulation. Machine failures lead to an abrupt stop of processing and start a repair process with subsequent repetition of a ramp up process. Weibull distributions were assumed with a 95.45% machine availability (2σ) during process time. Simulations were executed with different batch starting points and repeated 1000 times (Fig. 3). Machine failures disturb regularity of load curves during production process and thus causes a shift in energy demand. Results show an energy demand increase of 6% and 7% compared to results without machine failures for early batch starting points due to repetition of ramp up processes after machine failures (Table 4). However, later starting points are hardly affected by machine failures regarding energy demand per cell.

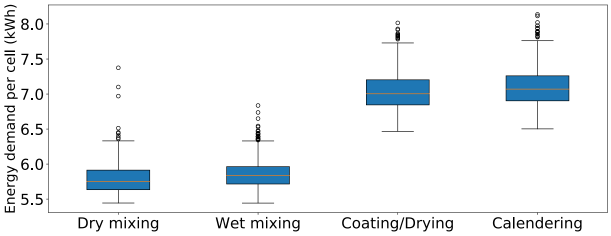

Fig. 3. Boxplots of energy demand per cell for electrode production regarding different starting points of new batches.

Table 4. Resulting mean energy demands per energy storage capacity [Wh/Wh] for different scenarios and different starting points of the next batch. Comparison of variation scenarios with S1.

Starting point	S1	S 2.1	S 2.2	S 3
Dry mixing	164.6	156.2	69.4	173.3 ± 6.3
		-5%	-58%	+5%
Wet mixing	164.9	156.5	69.7	175.4 ± 5.7
		-5%	-58%	+6%
Coating/ Drying	211.7	199.4	79.3	211.1 ± 8.1
		-5%	-63%	-0.3%
Calendering	212.6	199.4	80.2	212.9 ± 8.1
		-6%	-62%	+0.1%

5. Conclusion and Outlook

A multi-simulation paradigm approach is presented which allows determining the energy demand in battery production. The simulation was applied to the BLB of Technische Universität Braunschweig and covers both process machines and TBS and gives valuable inside into the specific energy consumption per process step. The energy demand per battery cell was determined to be 744.6 Wh/Wh (295.9 Wh/Wh by process machines and 448.7 Wh/Wh by TBS). It was shown that different starting points of consecutive batch material as well as different process parameters lead to a high variability in energy demand for electrode production per cell with energy values ranging from 69.4 Wh/Wh to 212.6 Wh/Wh (+306%). The results confirm that the energy requirement per battery cell and power curves during production are not static but rather strongly dynamic depending on boundary conditions and process parameters. Thus, the present work provides a possible explanation why current literature values vary immensely. Further, it was shown that simulation is able to quantify the effect of different energy saving potentials regarding different processes. Future research will focus on potential effects of different production scenarios on product quality and costs. In addition, further energy carriers (compressed air, gas, long distance heating) will be included in energy assessment of battery production.

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