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SIMULATION-BASED ENERGY REDUCTION FOR A LEAD-ACID BATTERY PRODUCTION WITH STOCHASTIC MATURATION AND DRYING PROCESSES

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ABSTRACT

The reduction of carbon dioxide (CO_2) emissions is a major goal of the European Union and energy storage is a core aspect to reach this goal. However, the production of lead-acid batteries is very energy consuming. Based on a case company production system and data, we develop a simulation model for the most energy-intensive lead-acid battery production steps, i.e., ripening and drying of lead plates. As both processes have some non-controllable stochastic aspects, the planned process times for both steps are a crucial factor for overall energy consumption. Too low or too high planned process times either lead to energy wasting for re-warm-up or to unnecessary energy consumption during processing. Simulation results reveal a significant energy reduction potential when optimizing planned process times, which increases when process uncertainty decreases. In addition, also the post-maturation and post-drying times are found to have a high influence on overall energy consumption.

1 INTRODUCTION

In the last decades, the reduction of carbon dioxide (CO_2) emissions had become a major goal of the European Union in order to achieve the climate-neutral goal by the year of 2050 (European Commission 2019). Besides the switch to renewable energies, the storage of energy is in the focus of politicians, managers and researcher. Therefore, the demand of different energy storage systems, such as lithium-ion batteries, nickel-metal hydride batteries or lead-acid batteries will substantially increase until 2030 according to (Statista 2021). Although, lithium-ion batteries are the main driver, lead-acid batteries are still used in various areas such as microgrids (Majumder et al. 2013), telecommunication power supplies or standalone energy systems (Zeng et al. 2016). The production process of lead-acid batteries is energy-intensive and often connected to emissions (Yilmaz 2022). The current study is based on an international case company producing lead acid batteries at a European production site. Basically, the production process of lead-acid batteries consists of four processes. At first, lead plates are cast by melting lead and a paste of lead oxide is pressed onto them. Afterwards the maturation and drying of the lead plates is performed in drying chambers through an energy-intensive heat treatment process. It is followed by the assembly of the lead-acid battery, which requires the lead plates. At last, the battery has to be filled with acid and put under voltage. The aim of the simulation study is to show energy reduction potentials at the most energy-intensive process step within the lead-acid battery production, which is the maturation and drying of the lead plates. Throughout the process, execution energy is added into the chamber and subsequently the lead plates. Energy input curves can illustrate the changes in energy input over the time. Since energy is added continuously, the planned process time of the maturation or drying determine the cumulated energy input, measured in kilowatt-hour (kWh). Concerning the maturation, the minimum required energy ensures the completion of chemical ripening. Whereas concerning the drying, the minimum required energy satisfies the required humidity level of the plates. On the one hand, a too long process execution consumes unrequired energy. On the other hand, a too short process execution causes rework and a restart of the process step, which also leads to additional energy input due to re-warm-up of the chamber. Consequently, by applying an optimized planned process time, unnecessary energy input as well as rework are prevented. However, because of external stochastic influences, it is not possible to exactly determine the minimum required energy for a batch and subsequently the optimum planned process time beforehand. These influences are for instance different humidity levels of the lead oxide paste, chemical attributes of the lead oxide paste, or temperature losses in chambers, which all lead to changes in the minimum required energy. In this paper, a simulation model of the respective production process is developed. As the exact distribution of minimum required energy is not known at the case company, we estimate the expected minimum required energy based on historical data and test different coefficients of variation respectively. In a numerical study, various planned process times for maturation and drying are tested to find optimized planned process times, which lead to a reduction of the energy input compared to the original times applied at the case company. In addition, the numerical study provides insights into the impact of varying the coefficients of variation for the minimum required energy on these optimized planned process times. The following research questions are addressed.

RQ1*: How can the maturation and drying process, including the energy input over time, be modelled?*
RQ2: *What is the energy reduction potential through simulation-based optimization of the planned process times and how do deviations from the optimum planned process times affect the energy consumption?*
RQ3: *How does the variance of the expected minimum required energy affect the optimum planned process times?*
RQ4: *What effect have predefined post-maturation and post- drying times on the optimum planned process times?*

The developed simulation model and performed numerical study lead to both, scientific and managerial contributions. The scientific contributions are, firstly, a depiction of the maturation and drying process including the resulting energy input over time, and, secondly, a heuristic approach, where the lowest energy input is found by testing various planned process times for maturation and drying. From an economic point of view, the decision makers get insights concerning the impact of different planned process times on the energy consumption, the trade-off between normal energy input versus energy input for rework, and the impact of different coefficients of variation on the optimal planned process times.

2 STATE OF THE ART

Basically, there are two main approaches to reduce the energy consumption in manufacturing. On the one hand, new energy-efficient machines can be acquired. On the other hand, energy-oriented production planning can be executed. The first approach, regarding the machine investment, is usually connected to high costs. Whereas, by applying an energy-oriented production planning, the energy consumption can be reduced in short-term and with little investment costs due to better understanding and control of the production system (Terbrack et al. 2021). A broad literature review by analyzing 375 research articles related to the topic energy-oriented production planning is conducted by (Terbrack et al. 2021). Based on the research articles they identified three key topics, which are energy consumption, load management and supply orientation. Furthermore, they presented economic and ecological objectives as well as constraints for every key topic. A part of production planning is scheduling, which covers short-term decisions. In (Uzsoy et al. 1994) dispatching and order release are characterized as the two main parts of scheduling. The goal of scheduling is to improve one or more possibly conflicting objective criteria while satisfying constraints, which are for instance capacity restrictions or waiting time limitations (Hopp and Spearman 2011). If improvement of energy performance indicators, such as energy consumption, is the main objective criteria for scheduling, it is referred as energy-efficient scheduling (EES) (Gahm et al. 2016). Energy-efficient scheduling has been analyzed and synthetized in a literature review of (Gahm et al. 2016). They proposed a new research framework to structure energy-efficient scheduling, based on 87 research articles. The framework has three dimensions, which are energetic coverage, energy supply and energy demand. The improvement of energy performance indicators based on scheduling can be achieved through solving an optimization problem, applying a heuristic, implementing scheduling rules, conducting a simulation study or a combination of them. Most publications solve an optimization problem, which determines production order sequences as (An et al. 2016), allocate resources (e.g., machines or personnel) as (Bruni et al. 2017) or do both as (Jiang et al. 2014). A heuristic is applied in (Gong et al. 2016) whereas, a rule-based approach is applied by (Choi 2016). A simulation study is conducted by (Cataldo et al. 2015) and (Mousavi et al. 2016). The simulation study approach is particularly suitable to depict stochastic processes and stochastic customer behavior. Moreover, simulation study facilitates to investigate different stochastic settings. Real-world production systems have to operate in such a stochastic environment (Bianchi et al. 2009). Since this publication is based on a real case company, a simulation study approach is selected. In this context the simulation model represents an abstracted and simplified Digital Twin of the underlying real production system. A comprehensive overview regarding the implementation of energy related aspects in simulation is presented by (Peter and Wenzel 2017; Poeting et al. 2019; Wenzel et al. 2018). Peter and Wenzel (2017) presented different methods to consider energy related aspects in simulation. Wenzel et al. (2018) summarized different simulation modelling methods related to energy and emissions. Moreover, the authors aggregated common objectives, requirements and implementation procedures of simulation studies. Whereas, (Poeting et al. 2019) presented an exemplary case studies and a classification approach to combine simulation with energy aspects.

3 PRODUCTION SYSTEM AND SIMULATION MODEL DESCRIPTION

To identify energy reduction potentials within the lead-acid battery production process, it is crucial to determine the most energy-intensive process step. Data driven analysis of the entire production process at the case company shows, that the maturation and drying process step exhibit the highest potential for energy savings. As such, this publication develops a simulation model that specifically targets this production step. The maturation and drying process step is performed in chambers. The company of the real-world case utilizes 31 chambers, with different pallet capacities. As this publication provides the first results of ongoing research, we only investigate one electrically powered chamber of the case company, which has a capacity of 16 pallet units. However, the model will be expanded in further research. *Figure 1* provides a comprehensive illustration of the studied production process also including information on the created simulation model, i.e., at which process step a random number is drawn and based on which distribution. In *Figure 1*, the process steps represented by gray shaded fields are energy-neutral, meaning that no energy is consumed during these steps. Whereas, in all other process steps, energy is consumed.

3.1 Production Order Generation and Energy Input Curves

The lead-acid batteries are produced in different variants based on a make-to-stock policy. The main components for the lead-acid batteries are the lead plates, which are composed of pure lead. Depending on the type of lead-acid batteries, different lead plate types are required. The simulation model used in this study generates production orders of lead plates, relying on the demand information of the case company from the preceding year. To define the variability at the generation of the production orders, the simulation model utilizes lognormal distributed interarrival times at the production order generation (see also (Felberbauer and Altendorfer 2014) and (Altendorfer et al. 2021) for application of lognormal distributions for production system simulation). Based on an ABC analysis, 15 lead plates accounting for 95 % of the load of the respective chamber are identified and simulated. The lot size, which is determined by the number of pallet units, is fixed in the simulation model for each lead plate type. If the lot size of certain lead plate types exceeds the capacity of the chamber, the production order has to be split into several batches, while ensuring high chamber utilization.

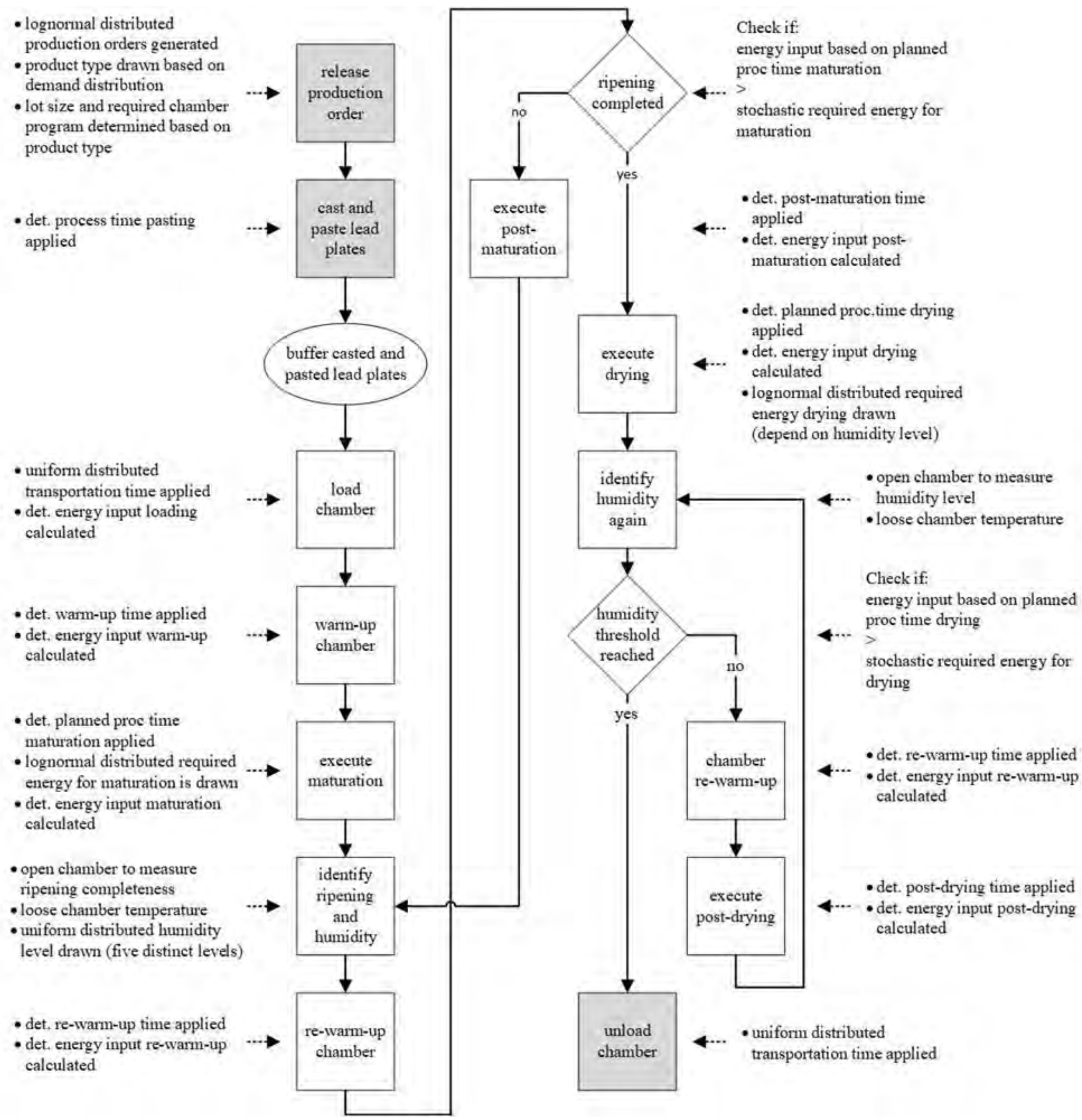

Figure 1: Process description.

Every lead plate type needs to be processed according to one specific chamber program; however, a chamber program can be used for several lead plates. A chamber program is a processing program, which determines the planned process times for warm-up, maturation, drying, post-maturation and post-drying, whereby the last two only occur in case of rework. Furthermore, the chamber program sets the targeted temperature and humidity throughout the duration of above listed process steps. The critical difference in the targeted temperature and humidity for a chamber program is whether it is designed for negative or positive lead plates. To attain the desired temperature and humidity, an energy input (measured in kWh) is necessary throughout the process execution. The course of the energy input throughout the process execution can be represented graphically by using energy input curves. *Figure 2* shows the energy input curve for a chamber program for negative lead plates, when post-maturation and post-drying are required. The energy input curve is based on primary energy consumption data from one electrically powered chamber of the case company. This energy input curve is integrated into the simulation model, allowing for accurate representation of the energy consumption.

As shown in Figure 2, the energy input at the start of the loading process step is high, as the chamber needs to be initiated. The same applies for the warm-up to achieve the start temperature and humidity in the chamber. At the maturation step, the chemical ripening is performed, which generates heat, especially at the beginning. Hence, at the beginning of the maturation process step, the energy input is lower since more heat is generated through the chemical ripening. For this reason, also the energy input for the warm-up is lower compared to the re-warm-up. Note, that the length of energy input curve depends on the applied planned process time. As this paper presents some preliminary results of a funded research project and detailed information is currently only available for negative lead plates, we assume the same energy input curve also for positive lead plates which is a limitation of this study. In further research more detailed energy input curves for positive and for negative lead plates will be applied when further data from the case company is available. However, the applied curve is still applicable to show the energy reduction potential of optimizing planned process times.

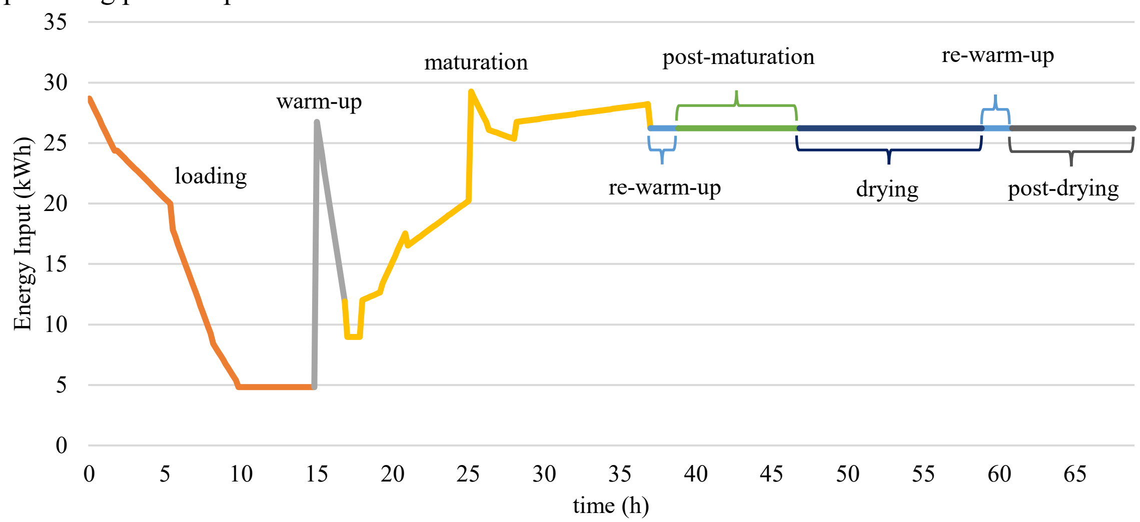

Figure 2: Energy input curve for negative lead plates.

3.2 Cast and Paste Lead Plates

After the release of the batch, the lead plates are cast using either the continuous casting or expand metal manufacturing technique. At the continuous casting technique, lead is melted and poured into a continuously moving mold, solidifying and forming the lead plates as it moves through the mold. Whereas, at the expand metal technique the lead plates are produced by simultaneously cutting and stretching a flat lead tape. Next, a paste of lead oxide and other additives is pressed onto the lead plates to establish the active material that is utilized in the battery cells. Since the casting and pasting process step is not the focus of this publication, only the delay of the pasting is depicted in the simulation model by using a deterministic process time. After this process step, the lead plates are batched to pallets and buffered.

3.3 Chamber Loading

The first process step of the maturation and drying process is the chamber loading. A forklift driver loads the pallets into the chamber. The simulation model considers the inherent variability and uncertainty in the loading process by employing a uniform distribution approach. This approach is based on expert information and provides an approximation of the process step. The start of the loading also implies the chamber start. Hence, an energy input occurs during the entire loading process, which is based on identical energy input curves for all five chamber programs. Based on the realized process time t and the energy input $E_{x,n,i}$ at each time period i (from the energy input curve in *Figure 2*), the cumulated energy input $\hat{E}_{x,n}$ for a batch can be calculated in the simulation model for *every* process step x (loading, warm-up, maturation, post-maturation, drying and post-drying) and every chamber program n as follows: $\hat{E}_{x,n}(t) = \sum_{i=1}^{t} E_{x,n,i}$.

3.4 Chamber Warm-up

After the loading is completed, the chamber has to be warmed-up to achieve the start temperature and humidity. As the required start temperature and humidity vary depending on the chamber program, the required energy input for the warm-up also varies accordingly. However, based on missing real-world data for different chamber programs, the curve shown in *Figure 2* is stretched or compressed to fit the planned process time of each chamber program and the basic shape is kept equal also for positive lead plates. Since there is no variability in the process execution, the realized process time is equal to the planned process time. This also applies for all the following process steps, except the unloading.

3.5 Maturation, Chamber Re-warm-up and Post-maturation

After the required start temperature and humidity is reached, the maturation is started. The objective of the maturation process step is to complete the chemical ripening of the lead plates, which requires energy. Throughout the maturation, energy is added into the chamber, and consequently to the lead plates, according to the energy input curves *(Figure 2)*. Hence, as stated in *section 3.3,* the planned process time of the maturation determines the cumulated energy input. The minimum required energy ensures a completion of the chemical ripening. However, as mentioned in the *Introduction,* different humidity levels of lead oxide paste and temperature losses in the chamber lead to deviations in the minimum required energy. The simulation model utilizes a lognormal distribution to determine the minimum required energy for a batch. Since explicit data on this minimum energy required is missing, the respective mean is estimated so that for the current planned process time and a coefficient of variation of 0.2, 98 % of batches need no post-maturation. Furthermore, different levels of uncertainty, i.e., coefficient of variation of minimum required energy, are tested. After the planned process time for maturation is complete, the chamber is opened, and the completion of the chemical ripening is verified as well as the humidity level is measured, as shown in *Figure 1*. In the simulation model, the cumulated energy input $\hat{E}_{maturation,n}$ is compared to the stochastic minimum required energy of the respective batch. If the cumulated energy input is higher or equal to the minimum required energy, the maturation is accomplished. Otherwise, post-maturation is required, which can be seen as rework. Before the post-maturation can begin, a re-warm-up of the chamber is necessary since temperature and humidity losses occurred during the check of the chemical ripening through opening the chamber. The post-maturation with the chamber re-warm-up is repeated until the chemical ripening is complete. Hence, multiple post-maturations may be required for a batch, as shown in *Figure 1*.

3.6 Drying, Chamber Re-warm-up and Post-drying

Once the chemical ripening is complete, the lead plates must meet a specified humidity threshold, which depends on the chamber program. To reduce the humidity level of the lead plates, the temperature and humidity are adjusted according to the chamber program, which leads to the transition to the drying process step. As at the maturation step, also here energy is added into the chamber, and consequently to the lead plates, according to the energy input curves *(Figure 2)*. The minimum required energy ensures a humidity level, which reaches the humidity threshold. Before drying, a re-warm-up of the chamber is necessary, because of the above-mentioned chamber opening. At the beginning of the drying process step the humidity level of the lead plates varies between batches randomly. This is because after the chemical ripening is completed, the humidity of the lead plates declines. Since the minimum required energy to complete the chemical ripening varies, some batches start to dry at the maturation process step. The humidity level of the lead plates is measured at the verification of the chemical ripening *(Figure 1)*. Moreover, temperature losses in the chamber also lead to additional deviations in the minimum required energy. These two aspects (different humidity levels and temperature losses) lead to deviations in the minimum required energy. To depict both aspects, the simulation model employs two distributions. At first the humidity of the lead plates is determined based on a uniform distribution at the beginning of the drying process step. Five distinct humidity levels are applied, i.e., "very wet", "wet", "normal", "dry" and "very dry". The expected minimum required energy, which is estimated similar to the maturation energy, is then determined based on the humidity level and the chamber program. Afterwards, the minimum required energy for a batch is calculated based on the expected minimum required energy, utilizing a lognormal distribution. To ensure the humidity threshold is reached, different planned process times are applied depending on the measured humidity level. Identically to the maturation process step, the planned process time determines the cumulated energy input (see *section 3.3*). After the planned process time for drying is complete, the chamber is opened, and the humidity is measured again, as shown in *Figure 1*. In the simulation model the cumulated energy input is compared to the minimum required energy, as at the maturation process step. Additionally, as at the maturation process step, post-drying with a re-warm-up is necessary, as long as the minimum required energy is not reached. Thus, also multiple post-dryings may be required for a batch, as shown in *Figure 1*.

3.7 Chamber Unloading

The final process step is the unloading of the chamber, which is identical to the loading, except that no energy is required as the chamber is switched off during unloading. Hence, in the simulation model only the delay time is depicted.

4 ENERGY REDUCTION POTENTIALS THROUGH PLANNING DECISIONS

The energy input at every process step depends on the realized process time. As previously mentioned, the process execution does not exhibit variability, resulting in matching the planned process times, except for the chamber loading and unloading process steps. The realized process time at the chamber loading and unloading is subject to the performance of the forklift driver and, we assume that it cannot be influenced by planning decisions. The planned process times for the chamber warm-up and re-warm-up cannot be altered without impacting the start temperature and humidity. Consequently, energy reduction potentials through planning decisions are only available at the maturation and drying as well as at the post-maturation and post-drying process step, for this single machine case.

A high planned process time at the maturation or drying increases the cumulated energy input and, therefore, the possibility to reach the minimum required energy for a random batch without post-maturation and post-drying respectively. However, a high planned process time also results in a cumulated energy input that surpasses the minimum required energy for some batches greatly. Thus, energy is wasted. Reducing the planned process time decreases the possibility of reaching the minimum required energy. This results in post-maturation or post-drying, and additional chamber re-warm-ups, since the chamber must be opened for each additional measurement (*Figure 1*). The same logic applies for the rework processes post-maturation and post-drying respectively. In case a high planned post-process time is applied, the possibility of multiple post-maturations or post-dryings is reduced. However, some batches surpass the minimum required energy after completing post-maturation or post-drying. Whereas a short planned process time leads to multiple post-maturations and post-dryings, which also results in additional chamber re-warm-ups.

Currently the case company applies a rather high planned process time at every process step which tries to avoid rework but might imply an energy reduction potential. To indicate this energy reduction potential of an optimum planned process time, a numerical study is conducted in this first simulation study using a simplified simulation model. Note that some of the data from the case company is still missing and, therefore, several parameters are approximated. However, the simulation model includes the inherent behavior of the single machine system with all relevant interrelations between planning and processing to indicate possible energy reduction potentials. As mentioned in *section 3.5*, the expected minimum required energy is estimated from historical data. However, it was not possible to determine the variance of minimum required energy. Therefore, different coefficients of variations are applied to investigate the effect on the respective optimal planned process times.

5 NUMERICAL STUDY AND RESULTS

To exploit the energy reduction potential based on setting the planned process times for maturation and drying, the respective parameters have been varied. To identify the optimal planned process times, a set of 15 possible values for maturation and drying is defined for each chamber program. The planned process times are defined based on the energy input curves so that a predefined percentage of the *expected minimum required energy* is provided. For maturation, the processing time factors $PT_M \in \{0.80, 0.85, \ldots, 1.50\}$ are applied. For example if PT_M =0.8, the planned process time in the simulation is set to 780 for chamber program 1, which leads to 80 % of the *expected minimum required energy* for this program. As mentioned in *section 3.6*, five different humidity levels can occur after the maturation step. Basically, the drying times are set according to the same logic as the maturation time, i.e., $PT_D \in \{0.80, 0.85, \ldots, 1.50\}$ is tested. However, if PT_D =0.8, the respective applied drying time in the simulation depends on the humidity level since the humidity level influences the *expected minimum required energy*. The following *Table 1* shows the applied planned process times for maturation and for “normal” humidity. For the humidity levels “wet” and “very wet” on average 25 % and 50 % more energy is required and the planned process times are increased accordingly. For the humidity levels “dry” and “very dry” on average 25 % and 50 % less energy is required, and the planned process times are decreased accordingly.

Table 1: Investigated parameters for planned process times.

Parameter description		Planned Process Time (min) to Provide Proportion of Expected Minimum Required Energy
chamber program 1	planned process time maturation	∈ {780, 820, 850, 890, 920, 960, 990, 1030, 1060, 1100, 1130, 1160, 1200, 1230, 1270}
	planned process time drying	∈ {410, 440, 460, 490, 520, 540, 570, 590, 620, 640, 670, 690, 720, 750, 770}
chamber program 2	planned process time maturation	∈ {780, 820, 850, 890, 920, 960, 990, 1030, 1060, 1100, 1130, 1160, 1200, 1230, 1270}
	planned process time drying	∈ {820, 870, 920, 970, 1030, 1080, 1130, 1180, 1230, 1280, 1330, 1380, 1430, 1490, 1540}
chamber program 3	planned process time maturation	∈ {1410, 1470, 1530, 1600, 1660, 1720, 1780, 1850, 1910, 1970, 2030, 2090, 2150, 2220, 2280}
	planned process time drying	∈ {690, 730, 770, 810, 860, 900, 940, 980, 1030, 1070, 1110, 1150, 1200, 1240, 1280}
chamber program 4	planned process time maturation	∈ {1410, 1470, 1530, 1600, 1660, 1720, 1780, 1850, 1910, 1970, 2030, 2090, 2150, 2220, 2280}
	planned process time drying	∈ {410, 440, 460, 490, 520, 540, 570, 590, 620, 640, 670, 690, 720, 750, 770}
chamber program 5	planned process time maturation	∈ {1410, 1470, 1530, 1600, 1660, 1720, 1780, 1850, 1910, 1970, 2030, 2090, 2150, 2220, 2280}
	planned process time drying	∈ {820, 870, 920, 970, 1030, 1080, 1130, 1180, 1230, 1280, 1330, 1380, 1430, 1490, 1540}

Concerning PT_M and PT_D a full factorial design, i.e., solution space enumeration, is applied which leads to 225 parameter sets tested for each scenario. To investigate the effect concerning the variance of the expected minimum required energy on the optimum planned process times, i.e., RQ2 and RQ3, ten scenarios with different coefficients of variation $CV \in \{0.05, 0.10, 0.15, \ldots, 0.5\}$ for the required energy are investigated, whereby the values for maturation and drying are set equal in each scenario. As a result, we obtained 2 250 different parameter combinations for each of the numerical studies. To answer RQ4, the experiment is repeated for 50 % reduced planned post-maturation and post-drying time, which leads to additional 2 250 parameter combinations and a total experiment size of 4 500 iterations. The simulation horizon for each run is 2.5 years with a half year as warm-up time. Applying 10 replications then leads to 45 000 simulation runs in the simulation experiment that have been performed in AnyLogic 8.8.1 with a run time of 7-9 seconds per run.

5.1 Effect of Planned Process Times

To analyze the energy reduction potential of different planned process times, in this section the *CV* is kept at 0.2. *Figure 3a* shows the overall energy consumption when the planned drying time is kept at PT_D =1.4 (the initial setting from the case company) and the planned maturation time PT_M is varied. *Figure 3b* shows the respective number of post-maturations. The results show that a lower PT_M than in the initial setting (red point) leads to a significant energy reduction potential, however, more post-maturation cycles are needed, i.e., a higher rework rate has to be accepted. The best trade-off between surpassing the minimum required energy for some batches and consuming energy for post-maturation, which was discussed in *Energy Reduction Potentials Through Planning Decisions*, is at a $PT_M = 1.05$. This approximated optimum leads to a planned maturation time, which provides 5 % more energy than the expected minimum required energy. Further as seen in *Figure 3a* and *3b* a PT_M lower than 1 increases the number of post-maturations significantly, which leads to higher overall energy consumption. The *Figure 3c* and *3d* show similar results as *3a* and *3b*, but for the case where the planned maturation time is kept at $PT_M = 1.4$ (the initial setting from the case company) and the planned process time for drying PT_D is varied. The results indicate a similar behavior of the energy reduction potential as discussed for the maturation. However, the approximated optimum planned drying time is at a $PT_D = 1.10$, which is slightly higher than for the maturation. Note that for both, maturation and drying, the results are solely focused on energy reduction. However, as shown in *Figures 3b* and *3d*, the number of rework cycles increases, which implies higher worker and chamber utilization as each rework cycle includes opening the chamber and measuring the batch status concerning ripening and/or humidity. In further research also this effect will be addressed.

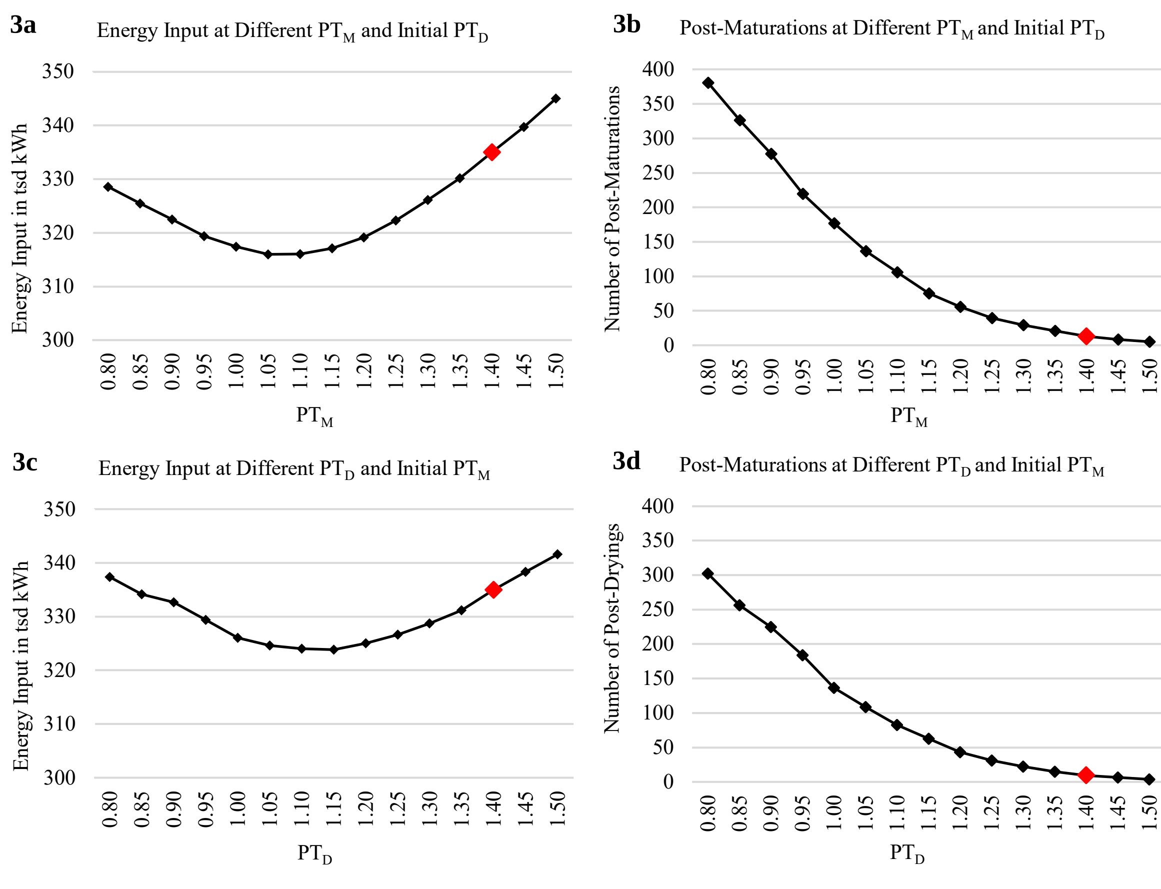

Figure 3: Effect of planned process times.

5.2 Effect of Uncertainty in Required Energy

The results in section 5.1 already indicate a high energy reduction potential when optimizing the planned process times. In this section the effect of uncertainty in the energy to be provided is evaluated, i.e., different *CV* values for the expected required energy are tested. *Figure 4a* shows the minimum energy consumption when optimized PT_M and PT_D values are applied in comparison to applying the initial setting of the case company for different CV values. Note that the CV is not yet known from data, so the results indicate the optimization potential related to the uncertainty. *Figure 4a* indicates that a higher CV leads to a higher overall energy consumption, since the required energy for a random batch fluctuates more, which leads to an increased deviation between energy input and required energy. However, optimized planned process times can substantially decrease the overall energy consumption compared to the initial setting, regardless of the applied CV. Particularly at low CV values, such as CV =0.05, there is a substantial energy reduction potential of 18 %. Furthermore, at CV =0.2 or CV =0.4, an energy reduction potential of 9 % is still present. Another interesting insight is that the slope of the overall energy consumption at optimized planned process times is initially high but flattens out as the CV increases. *Figure 4b* shows the approximated optimal PT_M and PT_D values as well as the resulting number of post-maturations and post-dryings respectively for each CV value. The results imply that a higher CV leads to lower planned process times for maturation and drying. Hence, the energy input during maturation respectively drying is lower and a greater proportion of the required energy is provided through post-maturation and post-drying, i.e., a higher rework rate is endorsed.

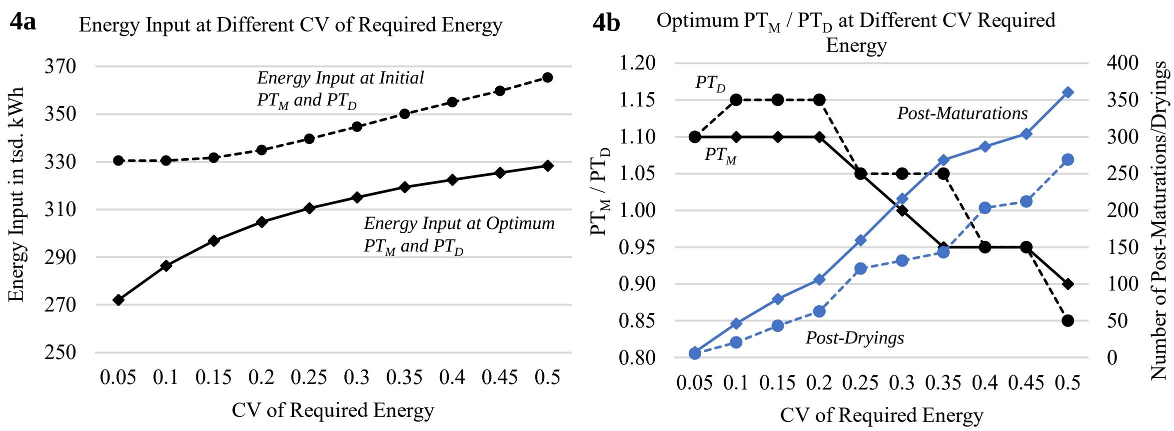

Figure 4: Effect of uncertainty in required energy.

5.3 Effect of Shorter Post-maturation and Post-drying Times

Since the length of post-maturation and post-drying times has to be traded-off against the energy loss from re-warm-ups, the following *Figure 5a* and *5b* show the effect of reducing the planned process times for post-maturation and post-drying by 50 %. As shown in *Figure 5a* the overall energy consumption can further be reduced regardless of the applied CV values.

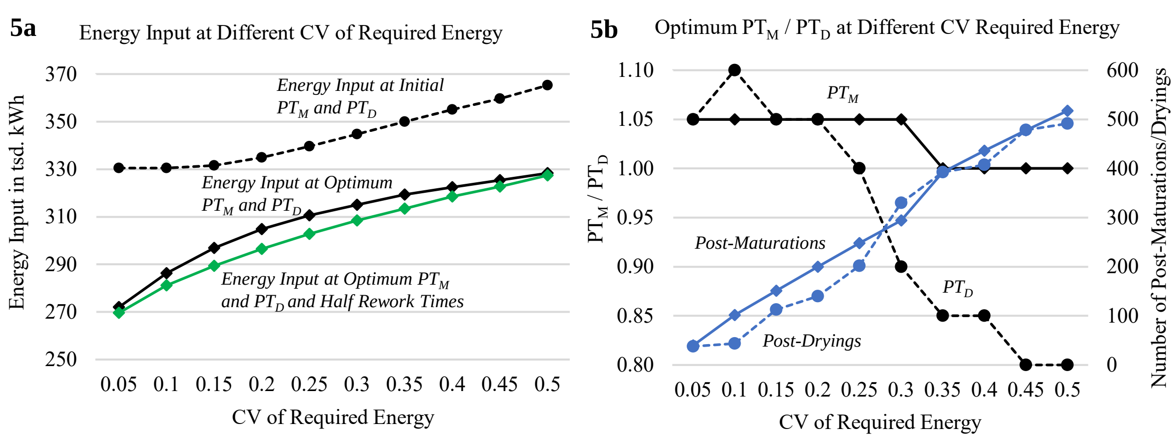

Figure 5: Effect of shorter post-maturation and post-drying times.

A high energy reduction potential in comparison to the original post-maturation and post-drying times is especially given for CV values between 0.2 and 0.35. Moreover, comparing Figure 4b and Figure 5b shows, that the reduction of the planned post-maturation and post-drying times leads to slightly lower PT values for drying, however, at high CV values the PT values for maturation increase. Both, shorter post-maturation and post-drying times and lower planned processing times for maturation and drying, result in a higher number of post-maturations and post-dryings respectively. This indicates that the current applied planned process times for post-maturation and post-drying at the case company are, from a pure energy consumption point of view, set too high, since although more energy loss from re-warm-ups occur, the overall energy consumption can be reduced. However, the best-found solutions imply more worker and chamber utilization which is a negative effect to be traded-off against the energy reduction. This will be addressed in further research.

6 CONCLUSION AND FURTHER RESEARCH

In this paper, a streamlined simulation model for the energy-intensive drying and ripening process of a lead-acid battery production is developed based on a real case company. For the respective process steps, an energy input curve over time is introduced, whereby the planned process times lead to a deterministic cumulative energy input for maturation and drying which is compared to a stochastic required energy for each batch. The planned process times for maturation and drying are optimized in a simulation experiment to minimize the overall energy consumption. The numerical results show that simulation-based approximation of the optimum planned process times for maturation and drying lead to a significant energy reduction potential compared to the initial applied setting at the case company. From a managerial point of view, the results indicate that lower planned processing times might be applied at the case company. Furthermore, the findings suggest that a higher variance in minimum required energy results in shorter planned process times. Consequently, a greater proportion of the required energy is provided through post-maturation and post-drying. In a further experiment, the planned post-maturation and post-drying times are reduced, and results show a further decrease in overall energy consumption, however, implying more post-maturation and post-drying cycles. A limitation of the current study is that some real data of the case company is still missing so that the minimum energy input needed is currently just estimated and in the streamlined simulation model only energy input curves for negative lead plates are applied. Nevertheless, the results show that simulating energy input for this process is a valuable tool to identify energy reduction potentials also for real world applications. Moreover, the negative effects of additional post-maturation and post-drying steps, which lead to higher worker and chamber utilization, are neglected. This effect will be studied in further work and further research should explore the effects of varying planned process times for post-maturation and post-drying. Also, the potential benefits of using sensors for a better estimation of the required energy will be addressed in the future. In addition, the simulation model will be expanded to parallel chambers to provide insights of energy reduction potentials through scheduling.

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