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Energy-Aware Production Planning with Renewable Energy Generation Considering Combined Battery- and Hydrogen-Based Energy Storage Systems

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Abstract

This study investigates the capacity of a developed production planning model to coordinate energy management within a hybrid energy system. The specific focus is on energy-intensive manufacturing firms utilizing renewable energy generation and energy storage. Unlike prior research in the field of energy-aware production planning, which revealed considerable cost saving potentials for the consideration of energy storage, this study considers a combined battery- and hydrogen-based energy storage with more realistic technology modeling. A formal mathematical model is developed as a mixed-integer linear program. Moreover, the cost saving potential of the combined energy storage system in energy-aware production planning is investigated based on numerical experiments. The experiments reveal that the implementation of the proposed planning approach saves significant costs compared to a baseline scenario. Up to 29.3 % cost saving potentials can be reached. In particular, the battery storage achieves significant energy cost savings while the hydrogen storage improves independence from fluctuating energy tariffs and availability of renewable energy. Possible model extensions are suggested to enhance the utilization of the proposed planning approach.

Keywords: energy-aware production planning; energy storage systems; hydrogen; mixed-integer linear programming; renewable energy generation

1. Introduction

Climate change and energy security currently pose some of the world's biggest challenges. Hence, governments react with policies that aim to reduce greenhouse gas (GHG) emissions and move towards a more sustainable future. The European Union (EU) has established the objective of becoming climate neutral by 2050 with the European Green Deal. This objective is linked with an interim goal of reducing greenhouse gas emissions by at least 55% by 2030, compared to 1990 levels. The industry sector plays an especially significant role in the decarbonization process, accounting for 25% of the EU's energy consumption (European Commission, 2021). In Germany, the renewable share of net installed electricity generation capacity already amounts to 62%. However, the actual public net electricity generation from renewable sources constitutes only 46% (European Environment Agency, 2021). This is due to the intermittency of renewable energy sources and their surplus energy generation potential when demand is low. The present expansion of renewable energies and the development of energy storage technologies are central measures of the German federal government's Climate Action Plan 2050 for decarbonizing the energy and industry sector in Germany (BMU, 2016). As a result, more decentralized energy structures are emerging in electrical energy systems on grid base and in production companies. In the industry context, these are considered as hybrid energy systems, which combine two or more energy conversion technologies to meet a common final energy demand (Palatel, 2017, p. 205). In the scope of this thesis, these are characterized by energy supply, energy consumption and energy storage. These components are described briefly in the following.

First of all, energy can be supplied via the energy market or by an on-site energy generation plant. Energy supply from energy markets is characterized by highly volatile en-

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ergy tariffs. This is due to trading mechanisms on various submarkets that trade energy at different time intervals from the actual delivery. At any given time, prices result from the momentary supply and demand of energy. As energy tariffs are based on predicted energy consumption, prices are high in times of high energy demand and correspondingly low in times of oversupply to create an incentive to consume energy over periods of high supply. The exchange markets for Germany are the European Energy Exchange EEX in Leipzig and the European Energy Exchange EPEX SPOT in Paris.

On the other hand, energy supply from on-site energy generation allows independence from fluctuating energy tariffs on the energy market. There are conventional on-site energy generation methods such as gas turbine usage or combustion engines combined with generators. However, the objective of this thesis is to consider renewable energy generation. Renewable energy sources have the potential to support decarbonization. Photovoltaic systems (PV) and onshore wind power plants are on average the least expensive technologies when considering all power plants in Germany (Kost et al., 2021). Although renewable energies promise to be cheaper and generate cleaner electricity than conventional energy plants, the biggest challenge is their highly uncertain and intermittent nature.

Secondly, in energy-intensive production industry, energy consumption mainly rises from energy-demanding processes. Flexibility instruments can be incorporated by production planning regarding job scheduling and shift planning. This is economically significant as the share of electrical energy costs accounts for 54% of energy costs in the energy-intensive production industry (Matthes et al., 2017). Operative planning and production management influence the exact amount and time of energy consumption, thereby significantly impacting energy costs.

Thirdly, the optimal utilization of increased shares of renewable energies requires the integration of energy storage systems (Sterner & Stadler, 2019, p. 134). Energy storage systems allow for temporally decoupling of energy generation and consumption within a considered system. By storing and extracting energy, the storage system enables energy generation or purchase in periods before consumption and thus independence from volatile prices at the spot market. Additionally, excess generated energy or stored energy might be sold to the external energy market, thereby providing additional revenue. In this investigation, electrochemical lithium-battery storage is considered representative for short-term energy storage, based on the corresponding cost-reduction potential in broad use and high efficiency (Sterner & Stadler, 2019, p. 658). According to the Fraunhofer Institute (2019), a Power-to-Gas hydrogen storage is considered as one of the only effective options for long-term storage and a potential energy carrier of broad use in the energy transition according.

The management of energy supply, energy consumption and energy storage presents a framework of interdependencies and decision relations. Energy-oriented or energy-aware production planning approaches (EAPP) coordinate decisions related to such frameworks. In literature, these model based planning approaches further include energy-awareness through objective criteria regarding monetary and non-monetary indicators for energy usage.

The objective of this bachelor thesis is to investigate the potential of combined battery- and hydrogen-based energy storage systems for energy-aware production planning with renewable energy generation. Further, analyzing the utilization of short-term and long-term energy storage systems and their potential to bridge daily - short-term - intermittency and inter-seasonal - mid-term - intermittency of renewables. This investigation aims to identify the optimal ratio of battery to hydrogen storage capacities in the context of energy-aware production planning.

The remainder of this thesis is structured as follows. First, the problem's characteristics and requirements are derived from the energy economic environment in Chapter 2. Secondly, existent literature streams in production planning regarding energy-aware production planning, renewable energy generation and energy storage systems are evaluated in Chapter 3. The model implementation including assumptions, notation and framework of the model is described in Chapter 4. A numerical study, including an investigation of the utilization of various storage capacity scenarios, is conducted and analyzed in Chapter 5. In conclusion, implications for practical application are derived and discussed and an outlook on potential future investigations is given in Chapter 6. The thesis is summarized in Chapter 7.

2. Characteristics of energy-aware production planning

In this chapter, special features of energy-aware production planning with renewable energy generation considering energy storage systems are analyzed. In Section 2.1, the problem is derived from the present context of the energy market (Subsection 2.1.1), renewable energy generation technologies (Subsection 2.1.2) and storage technologies (Subsection 2.1.3). The derivation of the conceptual model and analysis of requirements for the solution approach are conducted in Section 2.2.

2.1. Problem description

Energy-aware production planning aims to coordinate energy-oriented decisions within production systems. In the Scope of this thesis, the integration of a decentralized energy system is also considered. These usually consist of energy supply, demand and storage. Decentralized energy systems are emerging in industry due to their long-term advantages from ecological and economical points of view. Political pathways for a sustainable future linked to expected future measures are beginning to show verifiable impacts. Increasing numbers of companies are stating their compliance with politic pathways efforts such as the climate action plan. Many companies have publicly communicated their sustainability objectives, thereby ramping up the pressure for them to effectively fulfill the stated climate goals. This is reflected not only in investments in new energy-efficient production machines as well as the design of new production processes, but also in pilot projects increasingly incorporating solutions for greener production and sector coupling. Therefore, projections and concepts for a sustainable energy consumption include more decentralized energy structures. These decentralized energy structures depend on energy supply drawn from the energy market or on-site power plants, energy demand from energy-intense production processes and energy storage technologies. The context of these fields is characterized in the following sections.

2.1.1. Energy market

Since the liberalization of European markets in the 1990s electrical energy became a commodity. The unbundling of the energy sector led to the rise of numerous actors on the energy market. Here, wholesalers trade energy to customers that are either retailers or large energy consumers from industry. Large energy consumers in the German energy grid can benefit from wholesale prices on the energy market. But still, they depend on energy supply from the market. Energy supply from energy markets is characterized by highly volatile energy tariffs. This is due to the relatively high volume of traded energy in relation to available storage capacities combined with an mostly inelastic demand. Therefore, physical generation must follow energy demand (Schäfer, 2022, pp. 291 sq.). Trading mechanisms on various submarkets determine the actual market clearing energy price at any specific time based on the merit-order principle.

Figure 1 shows that the aggregated actual energy generation follows trends of the actual consumption. Differences between actual generation and consumption must be balanced by energy from the balance energy market. Usually, this is covered by additional storage or extraction of generated energy from pumped hydro or from fast-scaling gas-fired power plants. Trading energy on the internal energy market is another mean of assuring a stable energy grid.

Electrical energy is traded on the exchange and "over-the-counter". On the one hand standardized energy products are bought and sold on the exchange spot market. However, most of energy demanding companies close direct supply contracts with electricity producers considered as "over the counter" (OTC). In order to match energy demand with energy supply and employ generation plants cost-effectively, the exchange market offers electricity contracts for different time horizons. The futures market offers such contracts with up to six years, the day-ahead market until 12:00 pm of the previous day and intra-day market, which closes 45 minutes before delivery (Gate closure). OTC can be traded until 15 minutes before delivery. The different time horizons help balance supply and demand. Energy contracts from the futures market allow the prediction of energy consumption for a future point of time (Lenz et al., 2019). Energy tariffs are based on these predictions. That is, for periods of predicted high energy consumption, prices will be high, as there is a scarce supply of energy. In periods of low predicted energy demand, there is an oversupply of energy. As an incentive to consume energy and create demand, prices are low during those periods. By means of time-varying electricity tariffs, energy suppliers encourage companies to adapt their production schedules to match the power generation. They introduce so called time-of-use (TOU) tariffs as well as contracts on an hourly basis, such as real-time-pricing (RTP), that act in the range of the intra-day market and fulfill supply contracts in the very short-term (Bänsch et al., 2021). The different time horizons also allow energy producers and traders to plan their obligations over a longer period. The actual generation can also be adjusted to the real consumption as the delivery date of the electricity supply approaches. Additionally, the electricity price not only depends on national exchange markets, but is also influenced by international exchange of energy. The exchange markets for Germany are the European Energy Exchange EEX in Leipzig and the European Energy Exchange EPEX SPOT in Paris. Energy tariff data of past years is published by the Bundesnetzagentur (2020) on the basis of the day-ahead energy price. The day-ahead energy price depicted in Figure 2 indicates the aforementioned price fluctuations. On a daily basis (Figure 2a), the energy price is generally characterized by two peaks. The energy price tends to drop after a peak in the morning, until the price spikes again in the afternoon. This relation is given since a high share of the total energy demand is supplied by utility photovoltaic systems during the day as shown by Figure 1. Therefore, the cost-intensive energy production by conventional power plants can be reduced, which lowers the energy price. On a weekly (Figure 2b) and also mid-term basis, energy prices can differentiate drastically, which is due to developments on international energy exchange.

2.1.2. Renewable energy generation

On-site energy generation allows independence from fluctuating energy tariffs on the energy spot market. Schedulable and non-schedulable on-site energy generation may be differentiated. Moreover, on-site generation can be divided into conventional technologies and renewable energy generation (RGEN) technologies. Renewable energy sources have the potential to support decarbonization. Furthermore, renewable energy technologies are becoming increasingly economically applicable. Levelized cost of energy (LCOE) for renewable energy systems has been dropping in recent years. LCOE ranges of different power plants are depicted in Figure 3. The LCOE of PV systems range from 3.12 to 11.01 €cent/kWh, excluding value-added tax (VAT), depending on the type of system and solar radiation. The LCOE of onshore wind power plants in 2021 are between 3.94 and 8.29 €cent/kWh. The cheapest conventional power plants are combined cycle gas turbines (CCGT) with LCOE between 7.79 and 13.05 €cent/kWh. As a result, PV systems and onshore wind power plants are on average the technologies with the lowest LCOE in Germany, both among renewable energy technologies as well as all other power plants. Forecasts predict that even existing conventional fossil power plants will reach very high operating costs by 2030 at the latest, while the LCOE of new renewable energy plants will

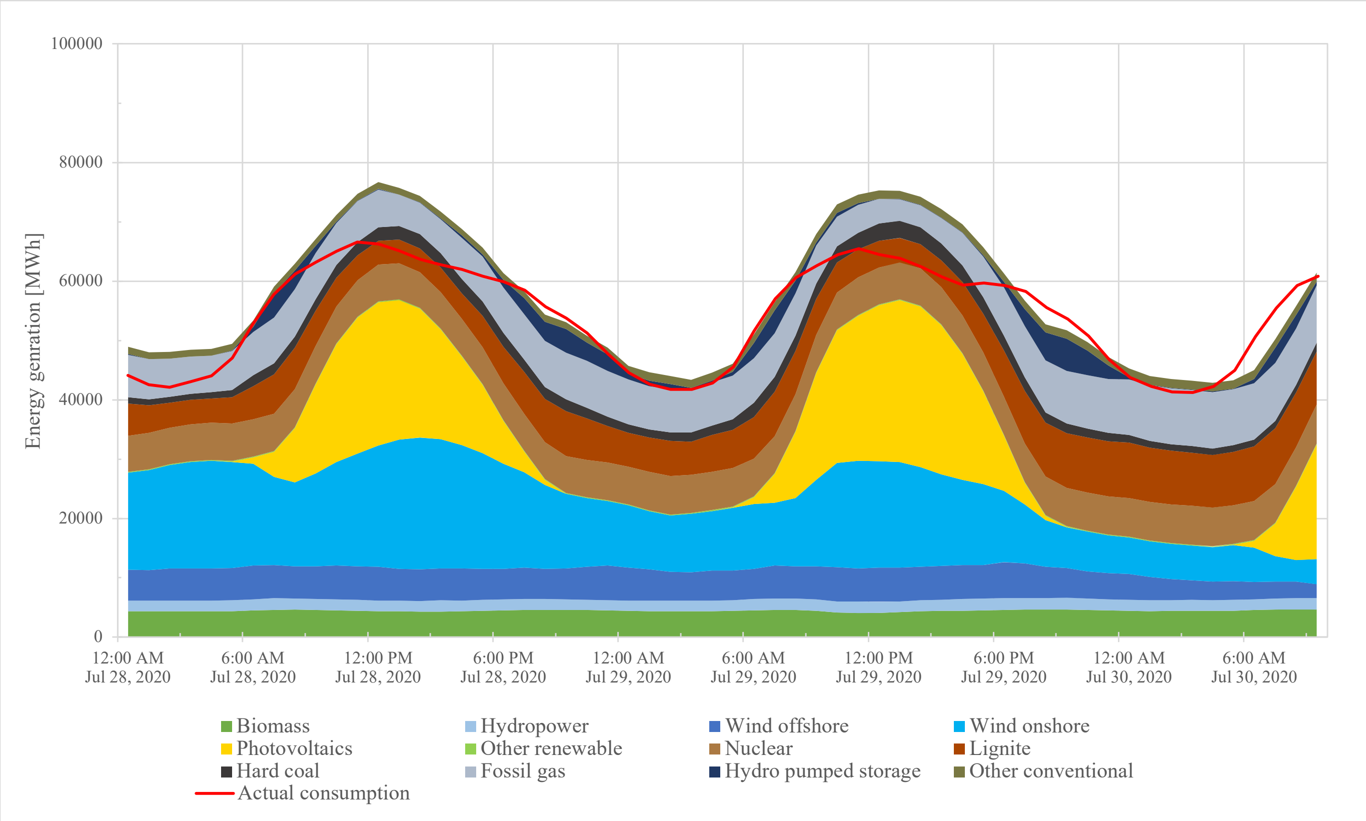
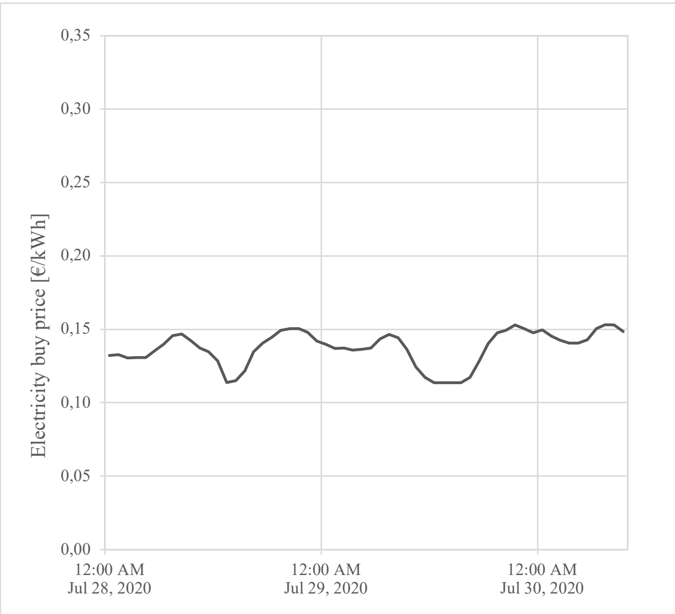
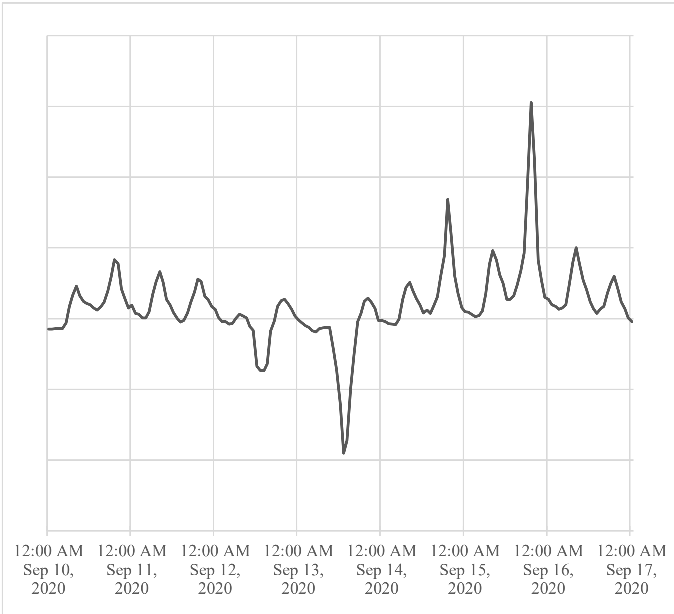


Figure 1: Fluctuating actual energy generation of renewable and conventional energy generation plants for demand fulfillment (own depiction based on data from Bundesnetzagentur (2020)).



(a) Daily energy price fluctuations



(b) Weekly energy price fluctuations

Figure 2: Day-ahead energy price fluctuations at European spot market for Germany with a surcharge of 0.1136 €/kWh (own depiction based on data from Bundesnetzagentur (2020)).

be significantly lower (Kost et al., 2021). Despite those advantageous economic and ecologic indicators and projections, renewable energies are characterized by their highly uncertain and intermittent nature. Therefore, RGEN are usually considered to be non-schedulable and lacking in terms of energy security and reliability. In the past, fluctuations in energy supply could be mitigated by demand-side flexibility, but renewables add to the inhomogeneous availability of energy. The renewable energy sources PV and onshore wind power are characterized by a highly intermittent nature. PV fluctuations occur on a daily basis as sun light is only available during daytime. Both wind and PV are also affected by inter-seasonal fluctuations of availability. The intensity of solar radiation decreases particularly during German winters. Therefore, solar energy generation undergoes corresponding decreases. In contrast, wind energy is more readily available during winters.

In energy-intensive production industry energy consumption mainly rises from energy demanding processes. These processes can be, for example, blast burn processes for steel production or the electrolytic process for aluminium production for example. There are pilot projects such as the sector coupling project "Windwasserstoff Salzgitter" (engl.: wind hydrogen) by the Salzgitter AG. The goal of such a project is to produce hydrogen through electrolysis from a network of wind turbines to reduce CO_2-Emissions during steel production. Similarly, in the transition to greener production processes and technologies, an increase of electrical energy demand is expected. Renewably generated electricity represents the basic energy source for decarbonizing various industry sectors. Be it for producing green hydrogen or delivering process heat, renewable electricity is considered as the substitute of fossil energy carriers. Thus, energy-aware decision making becomes increasingly important to distribute the available energy efficiently to satisfy the energy demand of the energy-intensive processes. For such production systems various energy-related decisions must be made while also considering new means of on-site energy sources.

2.1.3. Energy storage technologies

The optimal utilization of increased shares of renewable energies requires the integration of energy storage systems (Sterner & Stadler, 2019, p. 134). Energy storage systems allow for temporal decoupling of energy generation and consumption within a considered system. By storing and extracting energy, the storage system enables energy generation or purchase in periods before consumption and thus independence from volatile prices at the spot market. Additionally, excess generated energy or stored energy might be sold to the external energy market, thereby providing additional revenue. Typically, there are two types of storage systems: short-term and long-term energy storage. Short-term storage refers to storage over a duration ranging from several minutes to a few days. Long-term storage involves storing energy over a duration ranging from weeks to a year. Existent short-term storage systems are primarily characterized by high efficiencies and dis-/charging capacities but small storage capacities due to high investment costs. Long-term storage systems feature lower energy conversion efficiencies but larger storage capacities (Sterner & Stadler, 2019, p. 566). In this investigation, lithium-ion batteries are considered to be representative for short-term energy storage, based on their cost-reduction potential in broad use and high efficiency. A hydrogen storage is considered as one of the only options for long-term storage. Moreover, hydrogen plays a significant role as a potential energy carrier of broad use in the energy transition as it can be used in all three sectors - electricity, heating and transport (Sterner and Stadler, 2019, pp. 658 sq.; Fraunhofer Institute, 2019). For the Power-to-Gas conversion an electrolyzer utilizing Polymer Electrolyte Membrane (PEM) electrolysis (EL) is considered. The Gas-to-Power conversion is realized with a PEM fuel cell (FC) system. Both technologies have proven themselves for broad use in industrial, mobility and energy sectors (Yue et al., 2021).

The described components energy supply, energy consumption and energy storage provide the framework for EAPP. Due to the high share of electrical energy costs, energy-intensive production companies have an intrinsic motivation to become independent from fluctuating energy prices and availability. On-site renewable energy generation technologies and energy storage system (ESS) are key to achieving this goal. The framework and requirements for EAPP in the scope of this thesis are deepened in the following section.

2.2. Framework and requirements for energy-aware production planning

The framework of the production system considered in this thesis is illustrated in Figure 4. A production environment, energy storage system and renewables are all contained within the system boundary. The core element is the production environment, including machinery needed to run or support production processes. Workers operate the machines. The required amount of energy to run these energy-intensive processes is provided in three ways. Energy can be obtained from the energy market, supplied by on-site renewable energy generation or extracted from the ESS. The renewable energy generation features PV and a wind turbine. The ESS combines a battery storage and a hydrogen tank with an electrolyzer and fuel cell. The special features of the optimization problem are presented below.

The energy-aware production planning with renewable energy generation considering combined battery- and hydrogen-based energy storage systems (EAPP-BHS) requires three different planning approaches: job scheduling for the available machines, shift planning to employ operators at machines and decentralized energy management. Additionally, realistic characteristics of energy systems are considered.

Firstly, job scheduling in energy-aware production planning generates energy demand. The purpose of job scheduling is to assign jobs to a given set of machines, considering possible dependencies, with regard to a defined objective criterion. The production schedule determines the assignment of individual jobs to the machines informing about the order and the timing by which the jobs are completed on the

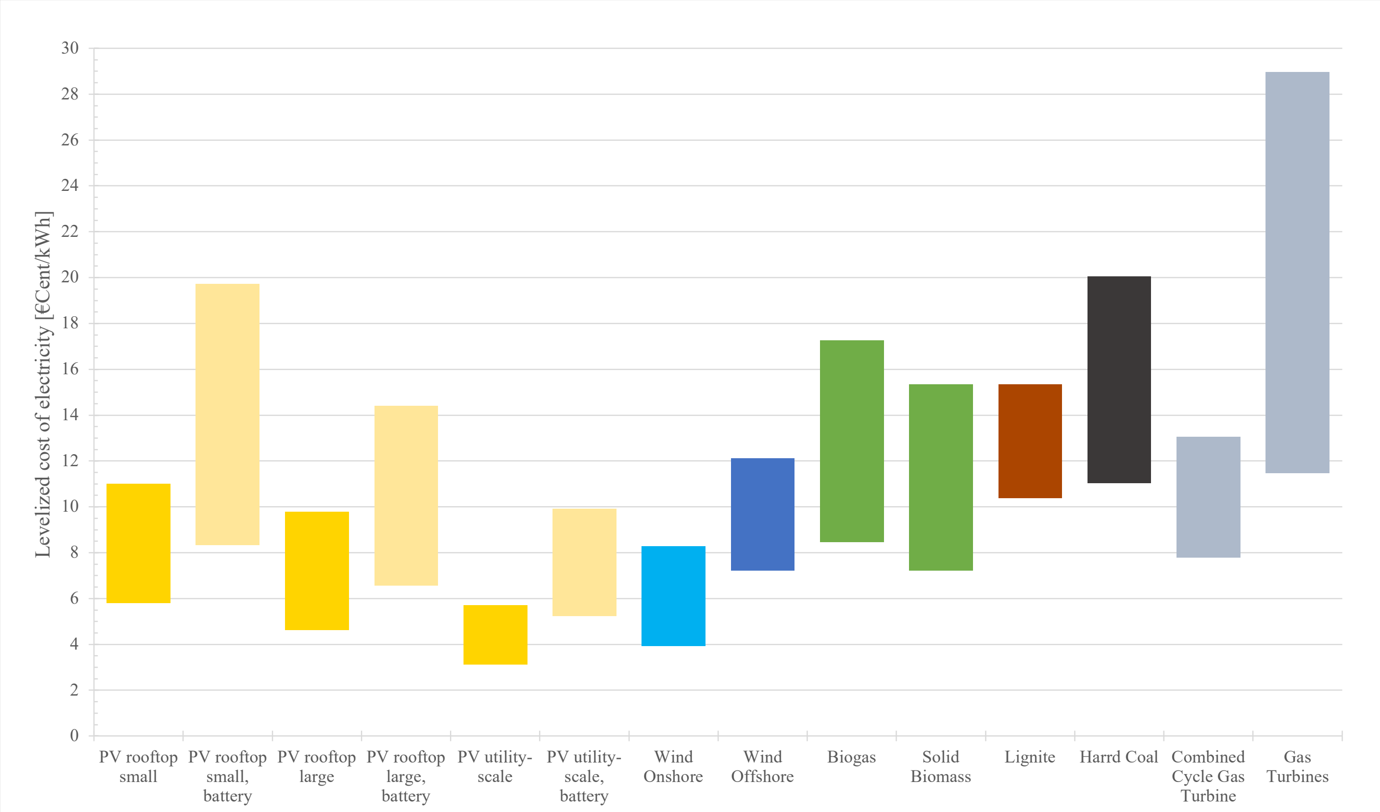


Figure 3: Levelized costs of energy of renewable energy technologies and conventional power generation plants at different locations in Germany in 2021 (own depiction based on Kost et al. (2021)).

machines. Decisions regarding starting times and lengths of different production states are included. The machine states determine capabilities, energy demand and if a worker is needed to operate the machine. In this consideration, five machine states are sufficient to describe manufacturing machines. The states include "off", "setup", "idle", "process" and "turnoff". In the off state, the machine cannot be used for production and has no energy demand. In the setup state, the machine is set up for the processing of a job in the subsequent period. The setup time is typically known and deterministic. In the idle state, the machine is on, but cannot produce. In the process state, the machine produces for which the machine must be set up. The processing of one job requires a certain amount of time. In the turnoff state, the machine is shut down and cannot produce. The energy consumption is based on these production-related machine states, thus influencing energy costs. (Liu et al., 2014; Copil et al., 2017).

Secondly, shift planning determines the assignment of shifts according to the number of machines to be operated. Machines in setup, process or turnoff mode require workers to operate. The focus is the optimal allocation of jobs within assigned shifts to optimally utilize the employed worker. An assigned shift itself is linked with day and daytime dependent salaries, thus influencing the labor costs. In combination, job scheduling and shift planning focus on the fulfillment of product demand within shifts during the planning horizon. However, in terms of energy-oriented decisions both planning approaches have conflicting objectives. On the one hand, job scheduling focuses on energy-efficient decision making on the quantity and timing of energy distribution. To minimize energy costs and fully utilize on-site renewable generation potential, energy focused job scheduling would follow the availability of renewable energy generation, which is characterized by high uncertainty and intermittency. In contrast, the objective of shift planning in the manufacturing industry is to establish recurring shift plans that homogeneously distribute workload. Hence, energy demand results from the operation of machines and the corresponding energy consumption within shifts regardless of energy prices and renewable energy availability.

Thirdly, decentralized energy management implies several decisions related to the distribution of renewable energy generation, energy storage system, external energy market and energy consumption. As described in Section 2.1 the energy market is characterized by energy traded at the same price only for short periods of time. For these short periods, energy-related decisions must be made regarding the purchase and retail of energy on the market, the distribution of on-site generated renewable energy, charging and discharging storage capacities of the energy storage system and energy consumption. Considering exact energy flows between the components of the energy system depicted in Figure 4, eleven decisions must be made regarding the quantity of energy exchanged between its components:

- Energy quantities that are bought from the grid, either being used for energy demand, stored in the battery or used to fill the hydrogen storage.
- Energy quantities that are sold to the grid, either absorbed from the renewable power generation, or extracted from the battery storage or hydrogen storage.
- Generated renewable energy quantities that charge the battery, fill the hydrogen storage or are used for energy demand.
- Stored energy quantities for production either from the battery or the hydrogen storage.

Additionally, considered energy flows are linked with conversion and dissipation losses when stored or extracted from the ESS. Storing electro-chemical energy in the battery is coupled with charging and discharging efficiencies as well as aging effects of the battery over time. The Power-to-Gas-to-Power conversion utilizing hydrogen as an energy carrier is tied to electrolysis and fuel cell efficiencies as well as dissipation losses. The production system is connected to the power grid for additional purchases of electricity and retail of surplus electricity.

To conclude, an EAPP should consider the conflicting objectives of job scheduling and shift planning. There are energy-aware decisions that must be made regarding the quantity and timing of energy flows both distributed within the system boundary and crossing the system boundary to trade with the energy market. Considering exact energy flows between components allows for better understanding of the energy management and renewable energy utilization in combination with the ESS.

3. Approaches to energy-aware production planning in literature

This section examines the relevant research streams in energy-aware production planning. Numerous papers incorporating energy-awareness and means of renewable energy into production management were recently published in this field. This is primarily due to the substantial amount of energy demand in industrial production and the increased awareness of environmental aspects found during literature review by Bänsch et al. (2021). Energy-aware production planning has notably been a main research subject of recent literature reviews conducted by Bänsch et al. (2021) and Terbrack et al. (2021).

On the one hand, Bänsch et al. (2021) propose a ten-dimensional classification scheme. From one perspective, they classify relevant articles in terms of their energy related scope, considering energy supply, energy demand and energy storage. From another perspective, classification dimensions refer to the modeling approach regarding objective criterion, the system of objectives, the manufacturing model, the mode characteristics, the planning horizon, the model type and the proposed solution method. Proposed literature includes on-site power generation environments that address the challenges of designing and operating production systems with open issues regarding mid-term energy procurement decisions and more realistic production costs. Moreover, the integration of multiple energy forms, e.g. electricity, on-site generation, chemically stored or pressurized energy forms, is proposed as another field for future research, especially considering the modeling of conversion technologies.

On the other hand, Terbrack et al. (2021) derive a more compact classification scheme revealing papers classified by their key topic: energy consumption, load management and supply orientation. The key topics emphasize the planning approach as either an optimization goal or as constraints within the considered approach. Further, they group together similar conditions into frequently found characteristics within EAPP to identify well investigated areas and gaps for future research. They propose the following five characteristics: various energy utilization factors, alternative production resources, heat integration, multiple energy sources and energy storage systems. As a result, they identify three main areas for future research. Firstly, they propose an increased integration of energy into mid-term production planning to potentially increase flexibility for energy-orientation in short-term planning. This puts heightened focus on ecological issues and reflecting that in planning approaches. Secondly, approaches addressing energy at multiple planning levels or across the entire planning hierarchy are identified as future fields of research potential. Thirdly, the combination of different dimensions related to energy use and different conditions for better energy efficiency should be investigated. Additionally, they describe notable research potential in the consideration of on-site energy generation and energy storage systems in EAPP.

Section 3.1 outlines general approaches to modeling energy-aware decision support. Section 3.2 goes on to present approaches to on-site energy generation in before Section 3.3 puts specific emphasis on managing energy storage systems in the scope of this thesis. Approaches considering characteristics of all streams are only presented in Section 3.3. Finally, the scope of this thesis is detailed in Section 3.4.

3.1. Modeling energy-aware decision support in production planning

This section presents a selection of papers modeling energy-aware decisions in production planning based on costs for total energy consumption and varying energy prices.

Ding et al. (2016) implement a parallel machine scheduling problem under a TOU electricity pricing scheme minimizing the total electricity cost. A time-interval-based mixed-integer linear program (MILP) formulation and a novel column generation heuristic were applied to solve the problem. Analyses of instances with different TOU settings discover tradeoffs between makespan and total energy costs that

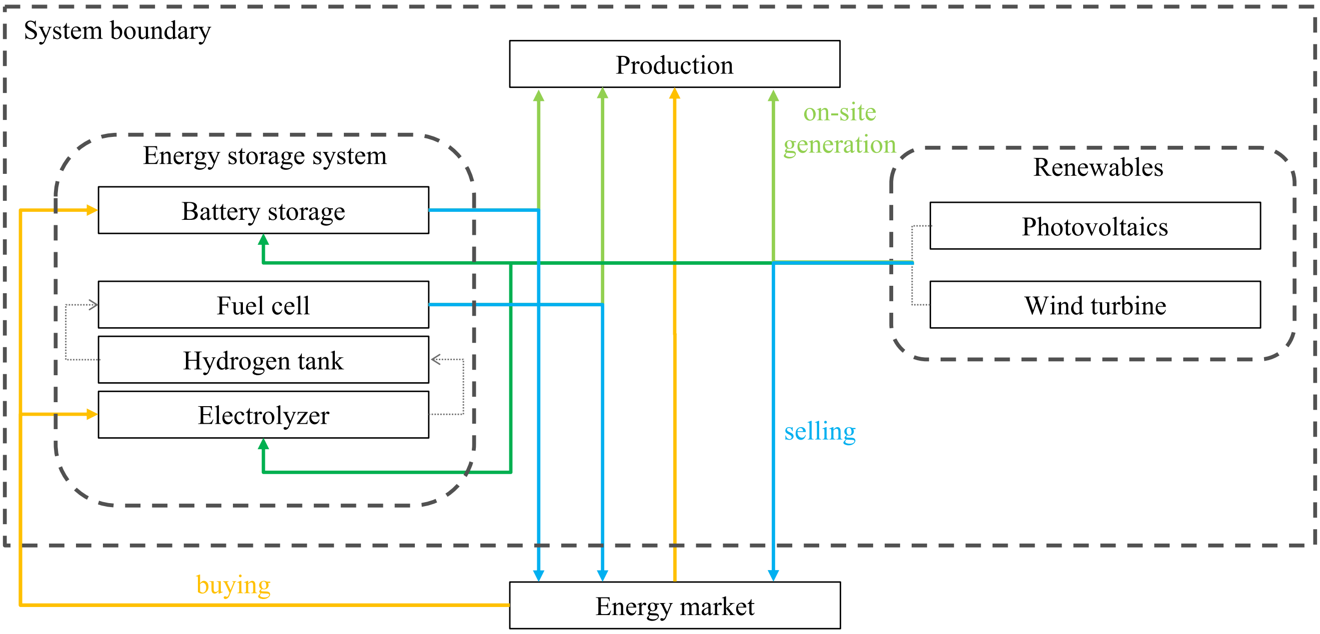


Figure 4: System boundaries of the considered production system including multiple energy sources and energy flows (own depiction).

could help make compromising decisions regarding these objectives. The authors suggest a further integration of cost and environmental impact of other resources into the optimization framework and see meaningful research potential in the consideration of scheduling problems under continuously changing energy prices.

Wichmann et al. (2019a) identify time-dependent energy prices as a neglected characteristic in energy-oriented planning approaches. Hence, the authors develop a general model formulation for the consideration of time-dependent energy prices in lot-sizing and scheduling. They derive a MILP, which introduces the missing considerations and investigates appropriate conditions for energy-oriented production planning. A numerical case study identified up to 9.69% of average energy costs and 1.04% total saving potential compared to conventional production could be identified. The authors also show that the best cost-saving potential is realized when there is high energy price volatility, high machine utilization and a diverse product portfolio. This particularly applies to energy-intensive industries. Future potential for research is seen in purely cost based planning approaches, faster solution procedure for larger instances and parallel-machine and multi-stage manufacturing approaches.

Gong et al. (2019) propose a many-objective integrated energy- and labor-aware flexible job shop scheduling problem tailoring a non-dominated sorting genetic algorithm-III (NSGA-III) for the optimization. To integrate energy awareness a state-based shop floor wide energy model is proposed with time-varying electricity and labor prices. The applied NSGA-III optimization method proves effectiveness for numerical experiments under RTP and TOU pricing. The methodology is suggested to serve as automated and enhanced decision support for factory managers to minimize production costs.

A paper considering hybrid flow shop scheduling with variable discrete production speed levels minimizing both energy costs and total tardiness was published by Schulz et al. (2020). Two multi-objective mixed-integer programming (MIP) formulations are given for the hybrid flow shop scheduling problem considering variable production speeds to reduce energy consumption at the expense of longer processing times. For the flow shop scheduling problem, two multi-objective mixed-integer program formulations are developed that consider variable production rates to reduce energy consumption. The conducted numerical case study reveals interdependencies between variable discrete production speed levels and energy costs, energy consumption and punctual delivery. For future work, it is desirable to develop heuristic solutions to solve larger problems within a reasonable computation time.

3.2. Modeling on-site renewable energy generation

Generally, on-site energy generation can be divided into schedulable and non-schedulable generation and articles on EAPP include schedulable, non-schedulable or both schedulable and non-schedulable energy generation. Renewable energy systems have become more popular in recent years as explained in Chapter 2. Abikarram and McConky (2017) investigate real time machine coordination for instantaneous load smoothing and photovoltaic intermittency mitigation. The paper focuses on power demand flexibility of industrial processes to reduce the variability in net demand. They develop a machine control logic that smoothens a machine fleet's power demand over time, decreasing the variability of net power sourced from the power grid of photovoltaic equipped factories. They proof the potential of smoothing strategies to mitigate the impact of renewable energy source intermittency on the grid.

Golari et al. (2017) aim to determine the production volume, the inventory level and the renewable energy supply in each period in order to minimize the total production cost including energy costs. The authors present a three-step solution method. First, they outline a deterministic planning model to reach the desired level of green energy penetration, before extending by a multi-stage stochastic optimization model considering the uncertainties of renewables and finally an efficient modified Benders decomposition algorithm for finding the optimal production schedule based on a scenario tree. Numerical experiments verify the potential of realizing high level renewable penetration through on-site and grid renewable integration. New models are needed for considering both product demand and RGEN uncertainties.

Dynamic scheduling of a flow shop with on-site wind generation for energy cost reduction under real time electricity pricing is tackled by Zhai et al. (2017). They develop a dynamic scheduling approach minimizing the electricity cost of a flow shop with a grid-integrated wind turbine. A MILP model is formulated for energy management. An autoregressive integrated moving average time series model is used to provide updated wind speed and electricity prices as real data becomes available. The authors show that the energy efficient manufacturing schedule provides a 14.6% lower cost and 524.14 kg less CO_2 compared to a condition without energy objective or wind turbine.

Biel et al. (2018) address flow shop scheduling with grid-integrated on-site wind power using stochastic MILP. A two-stage stochastic optimization procedure determines a production schedule and energy management decision for a flow shop system. The first stage incorporates a bi-objective mixed integer linear program that minimizes total weighted flow time and expected energy cost. In the second stage, energy management decisions are adapted to real-time wind power data. The conducted hypothetical case study reveals the feasibility of the proposed approach to effectively handle the uncertain nature of wind power. In addition, the consideration of energy-related GHG emissions is identified as a field for further study.

3.3. Models considering energy storage systems

In this section, energy storage systems are especially considered. Additionally, this section also presents papers with comprehensive modeling that incorporates varying energy prices, renewable energy generation and ESS.

An early paper considering the combination of time-dependent and machine-dependent energy costs, renewable energy sources and energy storage was published by Moon and Park (2014). Solar and wind are considered as RGEN. The developed constraint programming and mixed-integer programming approaches indicate reduction potentials for total electricity costs and energy costs. By their fundamental research they paved the way for future research in this domain.

Schulte Beerbühl et al. (2015) tackle scheduling and capacity planning of hydrogen storage. They demonstrate the feasibility of their derived heuristic approach for translating non-linear plant characteristics of the planning problem to a convex and continuous non-linear solution space. Compared to linear modeling of an electrolyzer more realistic and meaningful economic insight can be generated for electricity-to-hydrogen-to-ammonia plants. The heuristics can combine capacity planning and scheduling for intermittently operated chemical processes that link the electricity market at the chemical market.

A paper to introduce the concept of Smart Energy-Efficient Production Planning (SEEPP) for a general job-shop manufacturing system in the presence of a grid-connected micro-grid system (MGS) deploying wind power generation has been published by Golpîra et al. (2018). They utilize electrical and thermal storage considering technology characteristics such as (dis-)charge efficiencies. Optimization of the proposed Robust Mixed Integer Linear Programming model indicates cost saving potentials of 1.95% compared to conventional manufacturing systems. Among others, they propose the integration of other RGEN into the micro-grid, e.g. from fuel cell, PV or micro turbine.

Optimizing renewable energy generation to minimize the total electricity cost for sustainable manufacturing systems under time-of-use energy tariffs is the objective of the paper published by Cui et al. (2019). The model framework includes power input from electrical grid and a MGS. The MGS comprises of the RGEN technologies wind turbines and solar panels, as well as an energy storage system. A rolling horizon approach is adopted to deal with the intermittency of renewables. Probability and predicted energy generation are integrated within a nonlinear mathematical programming model. Numerical experiments show substantial benefits of incorporating renewable energy sources.

An Energy-Oriented General Lot-Sizing Problem regarding Energy Storages (EOGLSP-ES) was developed by Wichmann et al. (2019b). It extends their proposed model (Wichmann et al., 2019a) described in Section 3.1 and addresses the missing consideration of energy storage in energy-oriented production management approaches. A numerical study reveals cost saving potentials of more than 20% for the case of large energy storages. Furthermore, more realistic modeling of energy storages is highlighted as a future field for research.

Pham et al. (2019) propose a two-stage optimization program for multi-site and micro-grid planning with the objective to achieve net-zero energy operations. In the first stage, production scheduling is optimized to meet the uncertain demand at minimal operational costs. In the second stage, size and siting of the micro-grid systems are determined to cover the electrical load of multiple facilities. Results show that net-zero energy operation is feasible and affordable in locations of favourable wind and solar generation. Additionally, analysis reveal cost-effective implementation of battery systems combined with solar despite high capital costs of storage devices. On-site renewable energy integration is proving to be the ultimate key to realizing net-zero energy industrial operations.

Karimi and Kwon (2021) apply a MILP for their energy-aware production scheduling model incorporating on-site solar power generation and battery storage systems. More realistic technology characteristics, specifically dis-/charging rates and dis-/charging efficiencies are being adopted. Numerical experiments show that energy-aware scheduling can reduce energy costs by 23% and total costs by 7%. Utilization of solar energy generation and battery storage can save up to 36% of energy costs and 15% of total costs respectively.

Feng and Menezes (2022) develop a generalized mathematical model and characterize the optimal cost functions specially tailored for energy efficient renewable energy generation that utilize storage systems. They derive decision support for adopting actions at any state within the proposed wind-grid hydrogen system from a sensitivity analysis. Additionally, the authors propose combined energy storage technologies with various capacities, costs, response times and efficiencies as future research potential.

3.4. Potential for future research in energy-aware production planning

Table 1 provides an overview of all referenced scientific articles in Section 3.1-3.3. Although the presented literature is a limited selection, it contributes meaningful resources for future potential of research on the solution method and modeling of the incorporation of energy-awareness, RGEN and storage technologies.

The analyzed literature utilizes mathematical programming approaches. The most prominent representatives are MILP as well as mixed-integer non-linear program MINLP and stochastic (mixed integer) programming models. Furthermore, heuristic approaches are often applied to solve larger problem instances or in combination with mathematical programming in multiple stage optimization. Additionally, there is a smaller amount of simulation-based approaches. In the scope of this thesis, the problem is formulated as a MILP, as is commonly found in the reviewed literature and in practice because of its relative computational efficiency. Similar to the multi-stage optimization approaches presented in the literature (e.g. Pham et al. (2019), Golari et al. (2017)), a two-stage optimization approach is also employed in this work to consider mid-term and long-term planning horizons.

Energy-awareness in production planning can be addressed by employing various optimization objectives and constraints, as implied by the previous sections. Furthermore, different assumptions, conditions and capabilities enabling improved energy efficiency can be found. Including these characteristics in production planning approaches can increase flexibility for energy-aware production planning and improve energy utilization and the resulting costs. Minimization of total operational costs regarding labor costs and energy costs is reflected in the objective of the developed MILP in this investigation. This allows for simultaneous consideration of both objectives.

A substantial number of papers reviewed previously emphasize on-site energy generation and storage systems as fields of potential future research (see Table 1. Furthermore, the investigation of new combinations of dimensions related to energy utilization and exploration of different circumstances for improved energy efficiency are suggested. A missing consideration of a combination of short-term and long-term energy storage systems can be highlighted. Also, unrealistic technology characteristics are mentioned multiple times as potential for improved model extensions. The missing consideration of a combined battery- and hydrogen-based ESS is addressed within the scope of this thesis. The suggested approach also aims to depict more realistic technology characteristics. The specific implementation of the derived research scope for this thesis is presented in Chapter 4.

4. Model implementation

This chapter highlights the concept of the model implementation. The problem's assumptions are presented in Section 4.1, followed by the detailed formulation of the targeted mixed-integer linear program including definition of the notation in Section 4.2 and the description of the model framework in Section 4.3.

4.1. Assumptions

The model formulation is based on the assumptions presented in the following. The planning horizon is finite. The model approach aims to determine decisions with a time resolution of one hour. To simplify the application of the model, the long-term planning horizon is assumed to be one year with 52 weeks, equivalent to 8736 hourly periods. The demand for products is constant. A predefined amount of jobs has to be completed per week. This aids the focus on energy-aware decisions. The jobs feature deterministic and machine dependent processing times. No warehousing of products is considered. Jobs are processed without interruption. Within each period a machine is in exactly one state. The electrical power demand of each production-related machine state is known and deterministic. The total energy consumption is based on the time each machine spends in a specific state. Five types of machine states are sufficient including "off", "setup", "idle", "process" or "turnoff". Machines are shut down at the end of a week. Workers are infinitely available and have equal productivity rates. Salary rates are day and shift dependent. Salaries for morning and day shifts are assumed to be fixed costs due to contractually defined wages. Only night and weekend shifts are considered additional variable costs included in labor costs. Time-dependent energy purchase and offer prices are known from the day-ahead market at the stock exchange. Energy offer prices are 0.1341 €/kWh below energy purchase prices to account for surcharges and taxes. Energy input and output are balanced. Surplus energy not being stored is completely sold on the market. The energy exchange between grid and production system is not

Table 1: Overview of referenced papers.

	Ding et al. (2016)	Wichmann et al. (2019a)	Gong et al. (2019)	Schulz et al. (2020)	Abikarram and McConky (2017)	Golari et al. (2017)	Zhai et al. (2017)	Biel et al. (2018)	Schulte Beerbühl et al. (2015)	Golpîra et al. (2018)	Cui et al. (2019)	Wichmann et al. (2019b)	Pham et al. (2019)	Karimi and Kwon (2021)	Feng and Menezes (2022)
Energy generation															
Power grid (off-site)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adjustable on-site										✓					
Renewable energy (on-site)					✓	✓	✓	✓		✓	✓	✓	✓	✓	✓
Energy pricing															
Time-of-use (TOU)	✓	✓	✓	✓				✓			✓			✓	
Real-time pricing (RTP)			✓			✓	✓		✓	✓		✓			✓
Fixed price													✓		
Energy demand															
Processing	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓	✓	✓	✓
Non-processing			✓						✓		✓	✓	✓		
Factory setup															
Flow shop				✓			✓	✓			✓				
Job shop			✓												
Single machine	✓	✓										✓			
Parallel machines	✓				✓									✓	
Energy storage															
(P2P)										✓	✓	✓	✓	✓	✓
(P2X)									✓						
(P2X2P)										✓					✓
Objective criterion															
Energy costs	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓	✓
Energy consumption					✓										
Environmental aspects															
Labor costs			✓			✓									
Other monetary						✓			✓	✓		✓	✓		✓
Other non-monetary	✓		✓	✓				✓						✓	
System objectives															
Single objective		✓			✓		✓		✓	✓	✓	✓	✓	✓	
Multi objective	✓		✓	✓		✓		✓						✓	✓
Optimization approach															
MILP	✓	✓	✓	✓		LP	✓	✓	LP	✓		✓	✓	✓	
MINLP									✓		✓				
Heuristic	✓							✓	✓						
Stochastic						✓				✓	✓				
Simulation					✓										
Others	✓		✓												✓
Planning horizon															
Short-term (≤ 24 h)	✓	✓	✓				✓	✓				✓			✓
Mid-term (> 24 h)											✓				
Long-term (weeks/months)					✓	✓			✓	✓			✓	✓	

restricted in any direction. Dis-/charging rates and efficiencies of the battery storage system (BSS) are constant. The efficiency of the electrolysis is constant. The fuel cell efficiency is load dependent. To better represent the characteristics of this technology, a non-linear load-efficiency curve is assumed. Storage and extraction capacities of the hydrogen storage system (HSS) are identical. Aging effects and dissipation losses are realized by loss rates that reduce the amount of energy stored at the beginning of a period by a constant percentage rate. ESS can be charged and discharged in a single period. This is not omitted despite conversion losses to serve as a tool to validate the models decisions. Stored energy can be sold back to the grid. Renewable production is deterministic and known from publicly available data.

4.2. Notation

The following section introduces the notation of the proposed model. The notation is based on decision variables, parameters and sets. The relevant sets and indices for periods, jobs, machines, machine states and shifts are displayed in Table 2.

There is decision variables dedicated for job scheduling, shift planning, energy flows and storage summarized in table 3. The starting period of a job is defined by the binary variable Y_{ijp}. All periods occupied by the same job are marked by X_{ijp}. The machine's state is defined by W_{ips}. The integer variable V_q specifies the amount of workers assigned to a shift. According to the framework proposed in Section 2.1 every energy flow between the components of the production system is quantified by an individual decision variable. The storage variables determine the state of charge of the BSS and fill level of the HSS. The variable λ_{bp} is introduced to establish the non-linear load-efficiency relation between fuel cell load and output.

The model parameters are presented in Table 4. Different parameter specifications are introduced within the derivation of test instances in Section 5.1.

4.3. Model Framework

Based on the presented notation, the model framework is derived in this section. The model framework comprises the objective function and constraints categorized for energy flow balancing, job scheduling, shift planning, storage management of the battery and hydrogen tank as well as binary and non-negativity constraints.

Objective function

$$\begin{aligned} min\ TC = \sum_{p\in P} \beta_p^{buy} \cdot \left(E_p^{gr\to de} + E_p^{gr\to bat} + E_p^{gr\to el}\right) \\ - \beta_p^{sell} \cdot \left(E_p^{re\to gr} + E_p^{bat\to gr} + E_p^{fc\to gr}\right) + \sum_{q\in Q} V_q \cdot \alpha_q \end{aligned} \tag{1}$$

The objective function (1) minimizes the total relevant production-related costs, taking energy trading and variable labor costs into account. The objective function consists of three parts. Firstly, energy costs result from the aggregated amount of energy bought from the grid $\left(E_p^{gr\to de} + E_p^{gr\to bat} + E_p^{gr\to el}\right)$ evaluated with the energy buy price β_p^{buy}. Secondly, energy earnings result from the aggregated amount of energy sold to the grid $\left(E_p^{re\to gr} + E_p^{bat\to gr} + E_p^{fc\to gr}\right)$ evaluated with the energy sell price β_p^{sell}. Energy costs and earnings are aggregated for all periods. The third part includes the labor costs as the product of the amount of workers V_q assigned to each shift q and the specific wage for the shift q aggregated for all shifts.

Energy flow constraints

$$DE_p = \sum_{i\in M}\sum_{s\in S} W_{ips} \cdot e_{is} \qquad \forall\ p \in P \tag{2}$$

$$E_p^{gr\to de} + E_p^{re\to de} + E_p^{bat\to de} + E_p^{fc\to de} = DE_p \qquad \forall\ p \in P \tag{3}$$

$$E_p^{re\to gr} + E_p^{re\to bat} + E_p^{re\to el} + E_p^{re\to de} = re_p \qquad \forall\ p \in P \tag{4}$$

$$\begin{aligned} EC = \sum_{p\in P} \left(E_p^{gr\to de} + E_p^{gr\to bat} + E_p^{gr\to el}\right) \cdot \beta_p^{buy} \\ - \sum_{p\in P} \left(E_p^{re\to gr} + E_p^{bat\to gr} + E_p^{fc\to gr}\right) \cdot \beta_p^{sell} \end{aligned} \tag{5}$$

The energy flow constraints depict all relevant energy flows between components of the considered production system ensuring the exhaustive distribution of RGEN and fulfillment of energy demand. Constraint (2) calculates the energy demand (DE_p) in each period. Therefore, each machine's state-specific energy demand e_{is} is evaluated with the binary scheduling variable W_{ips} indicating the machine's state and aggregated for all machines. Constraint (3) ensures the feed-in of energy to meet the energy demand in each period. Therefore the energy input from grid ($E_p^{gr\to de}$), renewables ($E_p^{re\to de}$), battery ($E_p^{bat\to de}$) and fuel cell ($E_p^{fc\to de}$) is accumulated. Constraint (4) guarantees the distribution of the renewable energy production (re_p) to grid ($E_p^{re\to gr}$), battery ($E_p^{re\to bat}$), electrolyzer ($E_p^{re\to el}$) and demand ($E_p^{re\to de}$) in each period. Energy costs in constraint (5) are calculated as explained for the objective function (1).

Job scheduling constraints

$$\sum_{i\in M} \sum\nolimits_{p=1+}^{|P|-pt_{ij}+1} Y_{ijp} = 1 \qquad \forall\ j \in N \tag{6}$$

$$\begin{aligned} \sum\nolimits_{t=p}^{p+pt_{ij}-1} X_{ijt} \geq pt_{ij} \cdot Y_{ijp} \\ \forall\ i \in M, j \in N, p \in \{1,...,|P| - pt_{ij} + 1\} \end{aligned} \tag{7}$$

$$\sum_{j\in N} X_{ijp} \leq 1 \qquad \forall\ i \in M, p \in P \tag{8}$$

$$W_{i,1,0} = 1 \qquad \forall\ i \in M \tag{9}$$

Table 2: Sets and indices.

Index of period $p = 1, ..., \lvert P \rvert$	p
Set of periods p	P
Index of job $j = 1, ..., \lvert N \rvert$	j
Set of jobs j	J
Index of machine $i = 1, ..., \lvert M \rvert$	i
Set of machines i	M
Index of state $s = 1, ..., \lvert S \rvert$	s
Set of successor states s	T_s
Index of shift $q = 1, ..., \lvert Q \rvert$	q
Set of shifts q	Q
Subset of periods p in shift q	L_q

Table 3: Decision variables.

Machine i begins job j in period p	Y_{ijp}
Machine i processes job j in period p	X_{ijp}
Machine i in period p is in state s	W_{ips}
Amount of workers in shift q	V_q
Energy bought from grid [kWh]	$E_p^{gr\to de}, E_p^{gr\to bat}, E_p^{gr\to el} \geq 0$
Energy sold to grid [kWh]	$E_p^{re\to gr}, E_p^{bat\to gr}, E_p^{fc\to gr} \geq 0$
Renewable sources output within system [kWh]	$E_p^{re\to bat}, E_p^{re\to el}, E_p^{re\to de} \geq 0$
Stored energy for production [kWh]	$E_p^{bat\to de}, E_p^{fc\to de} \geq 0$
State of charge of the battery [kWh]	SOC_p
State of fill of hydrogen storage [kWh]	H_p
Break-point for linear interpolation of fuel cell load	λ_{bp}

$$W_{i,|P|,0} = 1 \qquad \forall\, i \in M \tag{10}$$

$$\sum_{s \in S} W_{ips} = 1 \qquad \forall\, i \in M, p \in P \tag{11}$$

$$\sum_{j \in N} X_{ijp} = W_{ip3} \qquad \forall\, i \in M, p \in P \tag{12}$$

$$W_{ips} \leq \sum_{k \in T_s} W_{i,p+1,k} \qquad \forall\, i \in M, p \in \{1, ..., |P|-1\}, s \in S \tag{13}$$

The job scheduling constraints ensure the scheduling of all jobs during the planning horizon. Constraint (6) guarantees that every job has a starting period once at one machine only. This should be realized at least the job's processing time before the last period of the planning horizon. Constraint (7) ensures the occupation of a machine for the whole processing time once started at the machine. If a job starts in a specific period ($Y_{ijp} = 1$), the binary scheduling variables W_{ips} are set to 1 for all periods ranging within the starting period and the completion period. That each machine processes only one job at a time is ensured by constraint (8). All machines are restricted to be turned off in the first period, turned off in the last period and only in one state at a time (constraints (9), (10), (11)). Constraint (12) forces the considered machine to be in operating mode when a job is produced. Constraint (13) only allows defined state transitions. In the subsequent period a machine's state can only be one of the states predefined by successor relations in T_s.

Shift planning constraints

$$\sum_{s \in \{2,4,5\}} \sum_{i \in M} W_{ips} \leq V_q \qquad \forall\, q \in Q, p \in L_q \tag{14}$$

$$LC = \sum_q V_q \cdot \alpha_q \tag{15}$$

The shift planning constraint (14) ensures a sufficient number workers assigned to a shift if machines need to be operated during periods of shift q. For all possible shifts of the set Q the corresponding periods L_q are scanned for machines in start up, shut down or processing mode. If these states occur for any of the machines, shift q is incorporated as many times as these states were counted. Labor costs in constraint (15) are calculated as explained for the objective function (1).

Battery storage constraints

$$\begin{aligned} SOC_p = & \left(1 - loss^{bat}\right) \cdot SOC_{p-1} + \eta^{bat} \cdot \left(E_p^{gr\to bat} + E_p^{re\to bat}\right) \\ & - \left(E_p^{bat\to gr} + E_p^{bat\to de}\right) / \eta^{bat} \qquad \forall\, p \in \{2, ..., |P|\} \end{aligned} \tag{16}$$

$$\begin{aligned} SOC_p = & \left(1 - loss^{bat}\right) \cdot soc^{init,first} + \eta^{bat} \cdot \left(E_p^{gr\to bat} + E_p^{re\to bat}\right) \\ & - \left(E_p^{bat\to gr} + E_p^{bat\to de}\right) / \eta^{bat} \qquad p = 1 \end{aligned} \tag{17}$$

$$SOC_{|P|} = soc^{init,last} \tag{18}$$

Table 4: Parameters.

Retail price (from grid) [€/kWh]	β_p^{buy}
Grid feed-in tariff (to grid) [€/kWh]	β_p^{sell}
Salary per worker and shift [€]	α_q
Energy demand of machine type i in state s [kW]	e_{is}
Processing time of job j on machine type i [ht!]	pt_{ij}
Renewable energy production [kWh]	re_p
Minimum usable battery capacity [kWh]	soc^{min}
Maximum usable battery capacity [kWh]	soc^{max}
Initial state of charge [kWh]	$soc^{init,first}$
State of charge in last period [kWh]	$soc^{init,last}$
One-way efficiency (dis-/charging) [%]	η^{bat}
Maximal dis-/charging per hour [kW]	$b^{max,rate}$
Loss of battery capacity per hour [%]	$loss^{bat}$
Minimum usable H_2-tank capacity [kWh]	h^{min}
Maximum usable H_2-tank capacity [kWh]	h^{max}
Initial H_2-tank fill [kWh]	$h^{init,first}$
H_2-tank fill in last period [kWh]	$h^{init,last}$
Efficiency of electrolysis [%]	η^{el}
Electrolyzer capacity [kW]	c^{el}
Fuel cell capacity [kW]	c^{fc}
Breakpoints for interpolation	b
Fuel cell load factor [%]	lf_b^{fc}
Fuel cell load	$l_b^{fc} = lf_b^{fc} \cdot c^{fc}$
Fuel cell efficiency factor in breakpoints [%]	ef_b^{fc}
Fuel cell efficient energy output in breakpoints	$eo_b^{fc} = ef_b^{fc} \cdot l_b^{fc}$
Dissipation loss of H_2-tank [%]	$loss^h$

$$soc^{min} \leq SOC_p \leq soc^{max} \qquad \forall\, p \in P \tag{19}$$

$$\left(E_p^{gr\to bat} + E_p^{re\to bat}\right) \leq b^{max,rate} \qquad \forall\, p \in P \tag{20}$$

$$\left(E_p^{bat\to gr} + E_p^{bat\to de}\right) \leq b^{max,rate} \qquad \forall\, p \in P \tag{21}$$

The battery storage constraints aim to model realistic features of a BSS. Constraint (16) ensures the energy balance of the battery state of charge (SOC_p). The SOC_p is increased by the amount of energy supplied from the grid and renewable sources ($E_p^{gr\to re} + E_p^{re\to bat}$) after considering conversion losses η^{bat}. The SOC_p is decreased by the amount of energy fed into the grid and demand ($E_p^{bat\to gr} + E_p^{bat\to de}$) after conversion losses η^{bat} respectively. This approach also introduces an aging rate ($loss^{bat}$) proportional to SOC_p. Constraint (17) updates SOC_p in the first period considering the initial SOC, which is an input parameter that has to be specified. Constraint (18) defines the SOC_p in the last period, which is an input parameter as well. Constraint (19) limits SOC_p to an lower bound soc^{min} and upper bound soc^{max}. Constraint (20) and (21) restrict charging and discharging to the maximum rate $b^{max,rate}$.

Hydrogen storage constraints

$$\begin{aligned} H_p = &\left(1 - loss^h\right) \cdot H_{p-1} + \\ &\eta^{el} \cdot \left(E_p^{gr\to el} + E_p^{re\to el}\right) - R_p^{fc} \qquad \forall\, p \in \{2, ..., |P|\} \end{aligned} \tag{22}$$

$$\begin{aligned} H_p = &\left(1 - loss^h\right) \cdot h^{init,first} + \\ &\eta^{el} \cdot \left(E_p^{gr\to el} + E_p^{re\to el}\right) - R_p^{fc} \qquad p = 1 \end{aligned} \tag{23}$$

$$H_{|P|} = h^{init,last} \tag{24}$$

$$h^{min} \leq H_p \leq h^{max} \qquad \forall\, p \in P \tag{25}$$

$$\left(E_p^{gr\to el} + E_p^{re\to el}\right) \leq c^{el} \qquad \forall\, p \in P \tag{26}$$

$$R_p^{fc} \leq c^{fc} \qquad \forall\, p \in P \tag{27}$$

The hydrogen storage constraints aim to model realistic features of a HSS similarly to the modeling of the battery storage. Constraint (22) ensures the fill level balance of the hydrogen tank (H_p). H_p is increased by the amount of energy supplied from the grid and renewable sources ($E_p^{gr\to el} + E_p^{re\to el}$) after considering conversion losses η^{el}. H_p is decreased by the amount of energy the fuel cell feeds into the grid and demand (R_p^{fc}) after conversion losses handled in a separate application of the Special Ordered Sets 2 (SOS2). This approach also introduces an dissipation rate ($loss^h$) proportional to H_p. Constraint (23) updates H_p in the first period considering the initial tank fill, which is an input parameter. Constraint (24) defines H_p in the last period, which is an input parameter that has to be specified as well. Constraint (25) limits SOC_p to an lower bound h^{min} and upper bound h^{max}. Constraint (26) and (27) restrict the throughput when filling the hydrogen storage by the electrolyzer (c_{el}) and extracting hydrogen for the Gas-to-Power conversion (c_{fc}).

Special Ordered Sets 2 (SOS2) for interpolation

$$\sum_b \lambda_{bp} = 1 \qquad \forall\ P, \lambda_{bp} \in SOS2 \qquad (28)$$

$$R_p^{fc} = \sum_b \lambda_{bp} \cdot l_b^{fc} \qquad \forall\ p \in P \qquad (29)$$

$$\left(E_p^{fc\to gr} + E_p^{fc\to de}\right) = \sum_b \lambda_{bp} \cdot eo_b^{fc} \qquad \forall\ p \in P \qquad (30)$$

The SOS2 comprise of outsourced constraints dealing with the non-linear efficiency behaviour of the fuel cell. The SOS2 is applied since the actual efficiency curve is approximated by a piecewise linear function. Constraint (28) guarantees that all breakpoints sum up to one. This allows the breakpoint to act as a weight for the output relation. Thereby the λ_{bp} of the set of breakpoints must be part of the SOS2 compliant breakpoints. At most two breakpoints can be nonzero in one period and must be adjacent in a fixed ordered list. In combination with Constraints (29) and (30) this enables interpolation of the energy throughput and efficient output of the fuel cell related to its load point. Constraint (29) calculates the hydrogen tank throughput by adding the product of two adjacent breakpoint values with their corresponding load at the breakpoint. Respectively, the Constraint (30) calculates the efficient fuel cell output. Here, by adding the product of two adjacent breakpoint values with their corresponding efficient energy output of the piecewise linear function.

Binary and non-negativity constraints

$$W_{ips} \in \{0,1\} \qquad \forall\ i \in M, p \in P, s \in S \qquad (31)$$

$$X_{ijp}, Y_{ijp} \in \{0,1\} \qquad \forall\ i \in M, j \in N, s \in S \qquad (32)$$

$$\begin{aligned} &E_p^{gr\to de}, E_p^{gr\to bat}, E_p^{gr\to el}, E_p^{re\to gr}, E_p^{bat\to gr},\\ &E_p^{fc\to gr}, E_p^{re\to bat}, E_p^{re\to el}, E_p^{re\to de}, E_p^{bat\to de},\\ &E_p^{fc\to de}, R_p^{fc}, SOC_p, H_p \geq 0 \qquad \forall\ p \in P \end{aligned} \qquad (33)$$

$$V_q \in \mathbb{N}^0 \qquad \forall\ q \in Q \qquad (34)$$

$$\lambda_{bp} \geq 0 \qquad \forall\ b \in B, p \in P \qquad (35)$$

The scheduling variables W_{ips}, X_{ijp} and Y_{ijp} are defined as binary variables. All energy flows ($E_p^{source\to sink}$), fuel cell throughput (R_p^{fc}), state of charge (SOC_p), hydrogen tank fill (H_p) and breakpoints (λ_{bp}) are defined as floating point decision variables. The number of workers per shift (V_q) is defined as an integer value.

Solving the data sets presented in Section 5.1 for the planning horizon of one year requires huge computational power. Therefore, the data is being split into weekly data sets. For a first mid-term planning horizon, the model is applied to 52 weekly data sets, which add up to one year. Weeks start on Wednesdays to actively force the model to consider higher labor costs on weekends. For a second long-term planning horizon, only the energy demand derived from job scheduling and shift planning is used as a basis to optimize the energy management for a whole year. In the second stage all job scheduling constraints ((6)-(13)) and shift planning constraints ((14)-(15)) are neglected. While all labor related decisions are fixed, the objective function minimizes energy costs as formulated in Equation (5). Energy management decisions are made for all 8736 hourly based periods.

5. Results of numerical experiments

This chapter outlines the results of the numerical experiments that were conducted. Open-source data in combination with the previously described modeling framework allow for reproducibility of the proposed model. The model is programmed using the open-source programming language Julia (version 1.6.3) including the Julia Mathematical Programming (JuMP) package. The Gurobi Optimizer (version 9.1.2) is used under an academic license to solve the model (using a MacBook Pro with 3.1 GHz Dual-Core Intel Core i5 and 16 GB RAM, allowing a MIP-gap of 5%, MIP-Focus of 1 and time limit of 30 minutes). In Section 5.1, the test cases and derivation of input data is described. The results are presented and discussed in Section 5.2.

5.1. Description of test cases and input data

To evaluate and analyze the behavior of combined energy storage and energy management in energy-aware production planning, the model is applied to illustrative numerical experiments for a hypothetical factory.

The manufacturing system is based on differently characterized milling machines proposed by Ding et al. (2016). The research observes the operation of old manual manufacturing machines alongside advanced ones in manufacturing companies. The advanced machines generally feature higher energy demand and faster operation speeds. Accordingly, in this hypothetical case two manual machines alongside one automatic machine are considered. The different energy consumption rates per period for the different machine states are summarized in Table 5. The fulfillment of 50 jobs with varying processing speeds on the different machine types is considered for the planning horizon of one week.

Table 5: Data for hypothetical manufacturing company including automatic and manual machine type specifications (based on data from Ding et al. (2016)).

Production			
Jobs J	$J = 50$		
Machines M	$M = 3$		
Periods P	$P = 168$		
Machines	Automatic	Manual Type I	Manual Type II
Energy demand process (100%)	282 kW	27 kW	24 kW
Energy demand setup (115%)	324 kW	31 kW	28 kW
Energy demand idle (5%)	14 kW	2 kW	1 kW
Energy demand turnoff (15%)	42 kW	5 kW	4 kW
Time needed for setup/turnoff	1 h		
Processing speed	1-6 h	2-12 h	3-13 h

Shift costs for workers are based on tariffs from the iron and steel industry presented in Table 6. Day and swing shifts are already planned and do not cause any additional costs during the work week from Monday to Friday. Therefore, only the remaining shifts cause additional shift costs.

The energy storage specifications shown in Table 7 are drawn and adapted from multiple sources to fit the hourly based planning horizon. The efficiency of electrolysis is drawn from the Silyzer 300 manufactured by Siemens energy. This is a modular system based on PEM electrolysis. The electrolyzer and fuel cell capacities are both at 2000 kW and is oriented at a pilot project of the APEX Group, which also manufactures customer specific hydrogen pressure storage. 2000 kW capacity allows for storage of peak renewable energy supply and energy extraction for peak energy demand. The non-linear efficiency behavior of the fuel cell is adapted from a fuel cell performance investigation incorporated in a hybrid electric vehicle as presented in Appendix 1. Loss rates for both the hydrogen tank and battery storage are negligibly small. However, they are considered in these numerical experiments to model a more realistic energy storage system based on values calculated in Appendix 2. The maximal dis-/charging rate of the battery system is set equal to the rated maximum usable capacity to fully utilize the short-term storage. For example FREQCON produces battery storage systems of various capacities with the specified one-way efficiency.

Energy prices and data for renewable energy production are extracted from the Bundesnetzagentur (2020). To observe mostly crisis-free data, 2020 is chosen as a reference year. The actual Germany-wide energy generation as visualized in Figure 1 is taken as an indicator for renewable energy availability. Here, the generation fluctuation of the incorporated renewable system is mapped with Germany-wide renewable energy generation capacity of onshore wind and photovoltaics. The peak power is allocated such that the aggregated renewable energy production of the considered year could cover the energy demand of the annual production regardless of the respective time availability. In this case, a 500 kWp wind onshore turbine and a 400 kWp PV system suffice this condition while being oriented at the wind to PV ratio of 60:40 to minimize their fluctuations (Sterner & Stadler, 2019, p. 135).

In order to observe effects of various storage allocations an initial set of combinations is optimized in a first stage, extended by further combinations of interest in a second stage and optimizations only with one storage type to complete the analysis. Cases 1 to 16 are optimized in the first stage. Four hydrogen storage capacities are combined with any of the four battery storage sizes shown in Table 8. The hydrogen tank capacities are chosen based on a first optimization utilizing an oversized hydrogen storage which revealed no deviation from the initial fill over 200 MWh. Therefore, a maximum hydrogen storage capacity of 400 MWh allows for positive and negative deviations. The other hydrogen storage sizes are chosen in linear degressive steps of 100 MWh. The initial set of battery storage capacities is chosen in steps of 200 kWh ranging around the peak energy demand of 383 kW. In the second stage, the initial cases are extended by even more battery capacities (Cases 17 to 28) to investigate the influence of the short-term storage in more detail, since higher cost saving potentials are identified for the short-term storage in the first stage. As the main goal of this work is to analyze effects of combined energy storage systems the optimizations with only one storage type are there to support the initial findings. All cases are compared to the optimization of a baseline scenario. This baseline scenario features no energy storage system with otherwise identical input parameters. Thus, it represents a production company that already utilizes renewable energy sources without means of storage.

5.2. Results and discussion

To validate and analyze the output of the developed model, various indicators and economic parameters are evaluated. Firstly, the influence of storage size allocation on the total operational costs is compared. Secondly, self-consumption rate (SCR), self-sufficiency rate (SSR) and energy surplus (SUP) are analyzed in more detail. Thirdly, the use of the combined ESS is investigated regarding utilization rates of storage capacities. Detailed investigations of optimized energy flows are consulted to provide further insights into energy management decisions.

Table 6: Day-dependent shift costs (based on data from IG Metall (2022)).

Shift costs per worker	Day shift	Swing shift	Night shift
Monday	0€	0€	234€
Tuesday	0€	0€	234€
Wednesday	0€	0€	234€
Thursday	0€	0€	234€
Friday	0€	0€	234€
Saturday	208€	208€	234€
Sunday	290€	290€	350€

Table 7: Nominal energy storage specifications (based on data from Siemens (2022)[1]; APEX Group (2022)[2]; Fletcher and Ebrahimi (2020)[3]; Töpler and Lehmann (2017)[4]; FREQCON (2017)[5]; (Sterner & Stadler, 2019, p. 300)[6]).

Hydrogen storage system	
Efficiency of electrolysis[1]	$\eta^{el} = 75.5\%$
Electrolyzer capacity[2]	$c_{el} = 2000$ kW
Fuel cell capacity[2]	$c_{fc} = 2000$ kW
Breakpoints for interpolation	$b = [1.0, 2.0, 3.0, 4.0]$
Fuel cell load factor[3]	$lf_b^{fc} = [0.00, 0.10, 0.60, 1.00]$
Fuel cell efficiency factor in breakpoints[3]	$ef_b^{fc} = [0.00, 0.54, 0.46, 0.37]$
Dissipation loss of H2-tank[4]	$loss^h = 0.00017\%$
Battery storage system	
Maximal dis-/charging per hour	$b^{max,rate} = soc^{max}$
One-way efficiency (dis-/charging)[5]	$\eta^{bat} = 98\%$
Loss of battery capacity per hour[6]	$loss^{bat} = 0.00035\%$

Table 8: Cases for hydrogen storage and battery storage capacity allocations in the first (gray) and second optimization stage (white).

H_2 \ Bat	0 kWh	100 kWh	200 kWh	400 kWh	600 kWh	800 kWh	1000 kWh	1200 kWh
0 MWh	base							
100 MWh		17	1	2	3	4	21	25
200 MWh		18	5	6	7	8	22	26
300 MWh		19	9	10	11	12	23	27
400 MWh		20	13	14	15	16	24	28

First, the total energy costs of all cases are compared to the optimization of the baseline scenario. The total cost calculation is based on the sum of the formulations (5) and (15). First optimizations showed that job scheduling and shift planning are mainly based on the availability of RGEN to minimize costly energy sourcing. Additionally, production plans and thus labor costs of the investigated cases do not change significantly (<2%) compared to the baseline scenario. Therefore, only total cost savings are considered, which are determined by effects of energy management. The results of the economic analysis are presented in Table 9.

Table 9 reveals four essential findings. First, increasing battery storage capacity leads to rising total cost savings. Compared line by line, the largest battery storage results in total cost savings that are 14.6 - 15% higher than in the respective scenario with the smallest installed battery capacity. This is also supported by the optimization with only battery storage showing an strict increase in savings potential. Second, there is a decreasing gradient of the savings potential with increasing battery storage capacity. The higher the capacity, the lower the increase in cost savings. By further increasing short-term storage capacity the saving potential approaches the share of total costs originating from energy purchase. Third, with increasing hydrogen storage capacity, the total cost savings increase slightly (<1%). The largest hydrogen storage capacity leads to slightly (0.4 - 0.8%) higher total cost savings than the respective scenario with the smallest hydrogen storage capacity. This is also supported by the optimization with only hydrogen storage showing a slight increase in savings potential (while 400 MWh does not fit the observation). Increasing short-term storage capacities influence total costs more significantly than increasing long-term storage capacities. This relation results from the more efficient utilization of short-term storage to decouple on-site energy generation from energy consumption, which is further investigated in subsequent analyses. Fourth, against expectations case 9, 13 and 14 (and the 400 MWh hydrogen storage case) do not fit the explored observations. This is due to a conflict of the short-term and mid-term planning approach. Whilst the mid-term optimization achieves results matching the observed patterns, the long-term planning approach deviates from the observed pattern.

Based on the economic analysis, large short-term energy storage systems, in combination with variously sized long-term energy storage, are of economic interest for production companies. The short-term storage capacity influences the total costs more significantly than the long-term storage capacities. The combination of a 1200 kWh battery and 300 MWh hydrogen storage shows the highest cost reduction potential with 29.3% compared to the baseline scenario. Furthermore, the proposed two-stage optimization approach reveals inaccurate performance for the individual cases 9, 13 and 14 which are treated as outliers for subsequent investigations.

In order to analyze energy-related effects, the solutions are compared regarding SCR, SSR and SUP as key performance indicators (KPI). The SCR (Equation 36) is defined as the share of on-site generated energy consumed locally. This includes renewable energy production for demand and stored energy minus stored energy capacities fed into the grid. The SSR (Equation 37) is defined as the share of local demand satisfied by on-site energy production, indicating the autonomy of the considered system (Luthander et al., 2015). On-site energy production comprises of renewable energy production for demand and stored energy minus extracted energy capacities stored from the grid. The SUP (Equation 38) is the proportion of the total amount of energy entering the system that is not used for production and the amount of energy needed for production (Wichmann et al., 2019b). Energy entering the system not used for production consists of renewable energy production sold to the grid and extracted energy capacities stored from renewables and sold to the grid. Energy conversion, dissipation and aging losses are considered as part of the system's demand. Mean roundtrip efficiencies are used to calculate temporarily stored energy quantities. The results of the presented KPIs are given in Table 10.

$$SCR = \frac{E_{total}^{re \to de} + E_{total}^{re \to bat} - E_{total}^{bat \to gr} + E_{total}^{re \to el} - E_{total}^{fc \to gr}}{re_{total}} \tag{36}$$

$$SSR = \frac{E_{total}^{re \to de} + E_{total}^{bat \to de} - E_{total}^{gr \to bat} \cdot 0.98^2 + E_{total}^{fc \to de} - E_{total}^{gr \to el} \cdot 0.334465}{DE_{total}} \tag{37}$$

$$SUP = \frac{E_{total}^{re \to gr} + \frac{E_{total}^{bat \to gr}}{0.98^2} + \frac{E_{total}^{fc \to gr}}{0.334465}}{DE_{total}} \tag{38}$$

Table 10 shows three essential findings. First, compared to the baseline scenario (SCR: 69.2%, SSR: 69.6%, SUP: 31.0%) all considered cases show significant improvement for all KPIs in relation to the considered allocation. Second, when comparing the largest battery storage capacity with the respective smallest battery storage capacity, SCRs slightly (0.1 - 1.5%) decrease, SSRs increase (5.2 - 6.9%) and SUPs slightly increase (0.2 - 1.6%). This indicates that the more short-term storage capacity is available, the less on-site generated energy stays in the system to fulfill the energy demand, but more is stored and sold to the energy market in later periods. Autonomy still increases as only excess storage capacities are offered for energy trading. In contrast to the decreasing SCRs and increasing SUPs for the combined optimization, in the battery-only cases SCRs increase and SUPs decrease. This reveals that that self-consumption and surplus are traded off in favor of better self-sufficiency, which increases more strongly in the combined cases than in the battery-only cases. Third, when comparing scenarios of larger hydrogen storage capacity to the respective scenario with the smallest hydrogen storage capacity, there are slight increases for SCRs (0.9 - 2.1%), SSRs (0.3 - 0.8%) and SUPs (1.0 - 2.2%) also evident in the hydrogen-only cases. In case the short-term storage can be fully charged and there is surplus renewable energy that cannot be sold profitably on the energy market, it is stored long-term and used during later more cost-intense periods. The long-term storage thus acts as a backup system, which increases the usage of on-site generated energy within the production system. The higher the capacity, the more energy is stored for later use. This behavior can be confirmed by the exemplary energy flows depicted in Figure 5, except that the model decides to charge the battery storage at the end of a period of high renewable energy availability. Given full information on renewable energy availability and price developments, the battery storage is charged as late as possible to avoid unnecessary losses due to aging effects of the storage, because the loss rate of the battery system is higher than the loss rate of the hydrogen storage. Additionally, in the range of period 481 to 673 the energy stored in the hydrogen storage is partly utilized to bridge the low availability of renewable energy. Added to that, during low demand phases, energy surplus is immediately stored in the battery storage to assist during subsequent more energy-intense production phases. Even though the mid-term planning approach scheduled less energy intense jobs during that time, additional energy is purchased from the grid. Before period 649, energy is even purchased at a comparatively low price to be stored in the battery and used in more pricey subsequent periods. Beginning from period 673, more renewable energy is available and used to refill the hydrogen storage. Energy is never stored and extracted from a storage in the same period due to conversion losses. The results of this analysis show that storage systems increase the utilization of on-site generated energy and system autonomy. In combination, the short-term storage does not only increase autonomy, but also energy trading through utilizing storage capacities to temporally store cheap renewable energy and generate revenue in times of high energy prices. Whereas the long-term storage acts as a backup to store any surplus energy for shifting on-site generated energy to later periods on a mid-term basis. In contrast to short-term storage, larger long-term storage capacity decreases energy trading.

Table 9: Total cost savings [%] optimized for a yearly planning horizon compared to the baseline scenario related to the allocation of hydrogen storage and battery storage capacity.

H_2 \ Bat	0 kWh	100 kWh	200 kWh	400 kWh	600 kWh	800 kWh	1000 kWh	1200 kWh
0 MWh	base	5.6	9.1	14.0	17.6	20.6	23.1	25.0
100 MWh	10.6	13.8	15.9	19.8	22.4	24.9	27.2	28.8
200 MWh	10.9	14.2	16.7	20.4	22.8	25.4	27.7	29.2
300 MWh	11.2	14.6	14.2	20.6	22.8	25.8	27.9	29.3
400 MWh	10.3	14.6	13.1	20.3	22.8	25.2	27.8	29.2

Table 10: Self-consumption rate, self-sufficiency rate and energy surplus [%] related to the allocation of hydrogen storage and battery storage capacity.

H_2 \ Bat		0 kWh	100 kWh	200 kWh	400 kWh	600 kWh	800 kWh	1000 kWh	1200 kWh
0 MWh	SCR	69.2	71.4	73.5	76.5	78.6	79.9	81.3	82.1
	SSR	69.6	72.2	74.2	77.0	79.0	80.4	81.7	82.4
	SUP	31.0	29.1	26.9	24.0	21.9	20.8	19.3	18.5
100 MWh	SCR	94.2	94.1	94.0	93.5	93.1	93.0	92.7	92.6
	SSR	79.9	81.3	82.1	83.5	84.1	85.2	86.0	86.5
	SUP	6.1	6.2	6.3	6.8	7.2	7.3	7.7	7.8
200 MWh	SCR	94.6	94.5	94.5	94.2	93.7	93.8	93.6	93.4
	SSR	80.1	81.4	82.5	84.0	84.5	85.7	86.4	86.9
	SUP	5.7	5.8	5.7	6.1	6.6	6.5	6.8	7.0
300 MWh	SCR	94.8	94.8	93.9	94.9	94.7	95.0	94.7	94.7
	SSR	80.1	81.5	80.3	84.1	84.7	86.3	86.8	87.4
	SUP	5.4	5.5	6.4	5.4	5.6	5.3	5.7	5.7
400 MWh	SCR	95.4	95.0	94.0	95.0	95.0	94.7	94.8	94.7
	SSR	79.8	81.6	80.2	84.0	84.9	85.6	86.8	87.3
	SUP	4.8	5.2	6.3	5.3	5.3	5.6	5.6	5.6

To analyze the use of the combined ESS, the utilization rates (UR) of storage capacities are compared. The URs are computed as follows:

$$H_2 - UR = \frac{\sum_{p \in P} H_p}{h^{max} \cdot 8736} \tag{39}$$

$$Bat - UR = \frac{\sum_{p \in P} SOC_p}{soc^{max} \cdot 8736} \tag{40}$$

Table 11 presents the utilization rates of the considered storage capacities. The UR is defined as the quotient of the aggregated actual storage fill and the aggregated storage capacity over all periods. Three main findings can be derived. First, hydrogen tank URs (H_2-UR) range between 71.1 - 77.8%. The storage fill level on average ranges near a three-quarter filling, which indicates its operation as a steady storage system able to deal with fluctuations. This is due to a small storing/extracting rate compared to its storage size. Comparatively, battery URs (Bat-UR) range between 26.8 - 36.4%. The short-term storage is identified by a strongly fluctuating SOC with partly emptied periods when there is low renewable energy generation, resulting in low URs. Battery-based stored energy quantities are mostly only stored to be used in subsequent periods. This is due to the dis-/charging rate, which is set equal to the storage capacity itself and allows for quick storage and extraction of stored capacities. Figure 6 depicts the exemplary utilization of the combined energy storage system for most of the cases. The hydrogen storage is filled until half of the year by storing large amounts of surplus on-site renewable energy and purchasing large amounts of energy from the energy market when prices are low. During pricey periods, the hydrogen is then converted back to electric energy and used to satisfy the energy demand of the production. In the second half of the yearly planning horizon, stored energy quantities also continuously provide energy during pricey periods and are reduced until the initial fill is reached at the end of the year. In contrast, the described fluctuating SOC of the battery storage is shown as well. Second, increasing battery storage capacity leads to higher battery utilization. Larger battery storage capacity results in a Bat-UR increase (8.3 - 9%) compared to the respective scenario with the smallest battery storage capacity. However, the effect on the hydrogen storage utilization is ambiguous as H_2-URs increase and drop (-4 - 1.3%) for the different storage capacities also seen for the hydrogen-only cases. Therefore, the sankey diagrams in Figure 7 reveal detailed information on the storage utilization. For the exemplary comparison of Case 20 and 28, the increase of short-term storage capacity leads to increased energy flows enter-

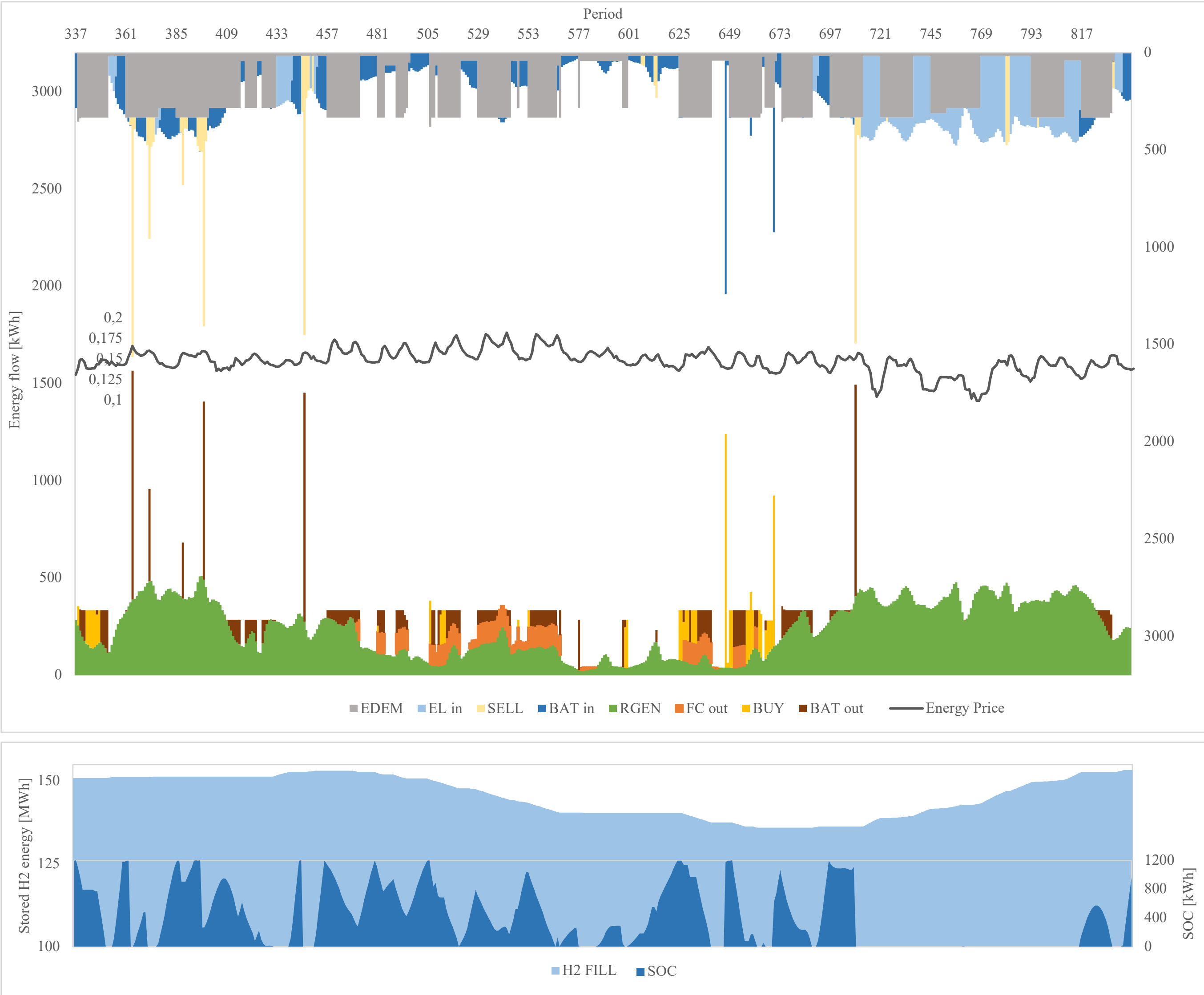


Figure 5: Exemplary energy flows and storage utilization of case 27 depending on energy price fluctuations and renewable energy availability of case 27 (300 MWh:1200 kWh) from period 337 to 840 (own depiction).

ing and leaving the battery storage. Because of its high efficiency, the battery is preferred over the hydrogen storage. In accordance with previously conducted investigations, there is an increased energy surplus that is sold on the energy market utilizing the battery storage system to generate additional revenue. Besides, the significantly increased energy flow entering and leaving the battery storage indicates the decoupling of RGEN and energy consumption, which is a reason for the explored cost saving potentials as less energy needs to be purchased from the grid. Furthermore, there is less energy surplus that can be stored long-term in the hydrogen tank. Interestingly, there is no clear increase in the battery-only cases as well. While the introduction of a hydrogen storage leads to lower utilization of the battery storage compared to the battery-only cases it also reveals that in combination battery storage focuses more intensely on short-term storage and only increases storage duration with increasing storage capacity. Third, increasing hydrogen storage capacities lead to decreasing URs of both storage systems. Bat-URs slightly (0.6 - 1.6%) decrease and H_2-URs decrease (0.3 - 5.6%) with larger hydrogen storage capacity compared to the respective scenario with the smallest hydrogen storage capacity. This indicates that larger long-term storage capacities reduce the demand for short-term stored energy quantities. Instead of being stored for a short period of time for short-term energy trading, energy quantities can be stored long-term to provide price hedging. Decreasing H_2-URs occur due to only slightly increasing energy flows entering and leaving the hydrogen tank, while the capacity increases more significantly for the considered cases, resulting in unused capacities. This relation can be seen in Figure 7 when comparing 7c with 7b. Moreover, the large gap at the output of the HSS can be seen, which on average accounts for 60% energy losses due to energy conversion and dissipation. In contrast, for the BSS these losses amount to an average of only 4%. This also explains the lower cost reduction potential for increased hydrogen storage capacities compared to battery storage.

In conclusion, three results can be obtained based on the conducted analyses. First, the utilization of combined energy storage systems reduces total costs by up to 29.3% compared to the baseline scenario. This is achieved by the combination of a 1200 kWh battery and 300 MWh hydrogen storage. This corresponds to a 1:250 ratio of battery storage capacity over hydrogen storage capacity and a 3:4:1000 ratio (renewable power over battery capacity over hydrogen capacity) in relation to the renewable energy plant peak power. The larger the storage capacities, the higher cost savings can be achieved. Even higher saving potentials can be expected if battery storage capacities are further increased. Battery storage capacity has a stronger effect on the cost savings than the hydrogen storage capacity. Second, autonomy of production systems can be improved. Whereas the combination of short-term and long-term show contrary effects. Increasing the capacity of short-term storage encourages energy trading. Whilst increased long-term storage capacity reduces energy surplus and increases autonomy. Third, battery storage is preferred because of its high efficiency. The hydrogen storage acts like a backup enabling mid-term price hedging in times of low renewable energy availability or high prices.

6. Conclusions and Outlook

This chapter surmises the results of this research, with Section 6.1 discussing implications for science and practical application and Section 6.2 outlining prerequisites for the proposed approach and directions for future work.

6.1. Practical implications

The problem investigated in this thesis is the utilization of combined battery- and hydrogen-based energy storage within an energy-aware production planning framework with existing renewable energy generation.

The proposed two-stage optimization approach suggests the utilization of combined battery- and hydrogen-based energy storage as typical representatives of short- and long-term ESS for production companies that utilize renewable energy power plants. On the one hand, highly efficient short-term energy storage should be incorporated in hybrid energy systems to achieve significant energy cost savings. On the other hand, to gain independence from the energy market and increase the utilization of on-site renewable generated energy, the combination with a long-term energy storage system like the considered hydrogen storage is beneficial. The explored cost-optimized 1:250 ratio of battery storage capacity over hydrogen storage capacity indicates the sufficiency of small-sized short-term storage and an optimized utilization of comparatively large sized long-term storage. Energy management decisions mainly have to be made based on renewable energy availability. In phases of low renewable energy availability (below peak demand), charging of the battery storage should be prioritized to bridge the daily RGEN fluctuations. At the same time, additionally extracted energy from the hydrogen storage has to feed the energy demand for production. Even sourced energy quantities from the market should be considered for short-term storage if prices are sufficiently low. In case storage capacities are exhausted or the extraction of energy from the hydrogen storage is no longer lucrative in respect of future refill opportunities, energy should be sourced from the energy market to satisfy energy demands. In phases of high renewable energy availability (above peak demand), refilling the hydrogen tank should be prioritized while the production demand can be sufficiently provided by RGEN and supplemented with short-term storage and extraction utilizing the battery system. If there is surplus energy supply characterized by low energy prices at the spot market, energy should be sourced from the grid to fill the hydrogen storage at low cost. Energy should only be sold to the grid if the company's own energy demands are satisfied and retail prices are sufficiently high. This can even be short-term stored energy that is sold when retail prices are high (energy arbitrage). These conclusions deserve a word of caution as they depend on the specific scenario chosen for this investigation, which is further discussed in Section 6.2. Unlike material costs and the predominant share of labor costs, energy costs can be actively influenced by management decisions. Therefore, the consideration of energy-aware production planning plays a significant role for saving costs of energy-intensive production companies. If connected to a decentralized energy network, the considered production system acts as a so-called "prosumer": The production company not only consumes energy, but also generates energy for the grid. Energy is either immediately fed into the grid when there is energy surplus from on-site renewable energy generation and sold on the energy market, or it is temporarily stored and offered to the market when retail prices are sufficiently high. Furthermore, in case of reduced energy demand of the production system due to more efficient processes or fewer machines, renewable energy plants still generate electricity. This surplus electricity can be used manifold. The model shows that stored energy can be sold profitably in later periods. Full information on the availability of renewable energy and energy price fluctuations allows for the sale of stored energy quantities at the right timing for the profit margins explored by the model optimization. However, profit margins of lower extend could still be achieved if energy management monitors energy demand and price fluctuations to offer energy in times of relatively high prices. Unused storage capacities could also act as decentralized energy storage for the electricity grid. This capability could be used for smoothing voltage fluctuations and stabilize the electricity network. The surplus stored hydrogen could also be sold on future markets for hydrogen as proposed by Fraunhofer Institute (2019). This opens a second opportunity of generating revenue. As a result, the considered production system adds to a more decentralized energy system and enhances sector-coupling with the trade of green hydrogen.

To conclude, the utilization of combined ESS implemented by the proposed energy-aware production planning

Table 11: Utilization rates of storages [%] related to the allocation of hydrogen storage and battery storage capacity.

H_2 \ Bat		0 kWh	100 kWh	200 kWh	400 kWh	600 kWh	800 kWh	1000 kWh	1200 kWh
0 MWh	H_2-UR	base	—	—	—	—	—	—	—
	Bat-UR		43.2	42.2	42.3	42.7	42.9	43.3	43.6
100 MWh	H_2-UR	74.3	75.4	75.8	76.3	76.2	75.8	76.2	76.7
	Bat-UR	—	28.1	29.2	31.7	33.4	34.9	36.2	36.4
200 MWh	H_2-UR	77.3	77.8	77.6	77.0	76.9	76.3	76.7	76.7
	Bat-UR	—	27.5	28.9	31.6	33.0	34.8	35.7	36.4
300 MWh	H_2-UR	76.5	76.6	76.2	76.9	76.8	76.9	77.3	77.0
	Bat-UR	—	26.8	28.3	30.2	32.3	34.1	35.1	35.8
400 MWh	H_2-UR	75.9	75.1	75.0	73.0	73.1	71.5	71.3	71.1
	Bat-UR	—	26.8	27.6	30.2	32.1	33.9	34.9	35.8

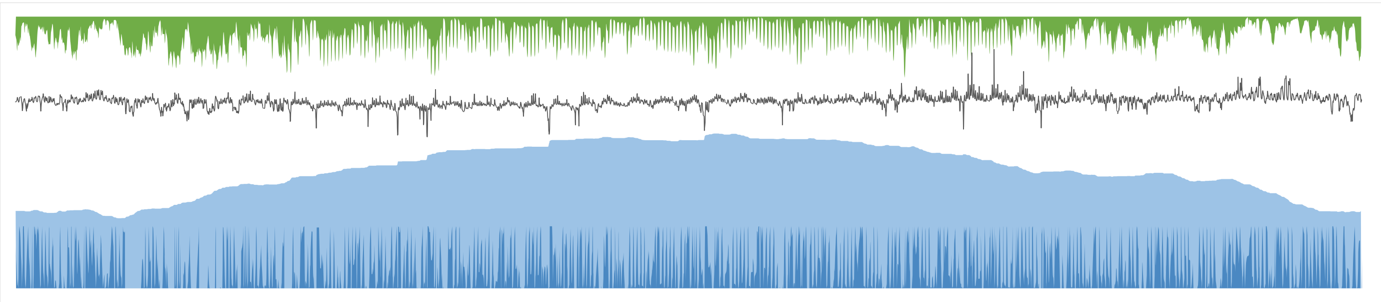


Figure 6: Exemplary energy storage utilization of case 27 with grey line: energy price level (0.03 - 0.31 €/kWh), light blue: hydrogen storage fill (136000 - 300000 kWh), blue: SOC (0 - 1200 kWh), green: RGEN (6 - 696 kWh) (own depiction).

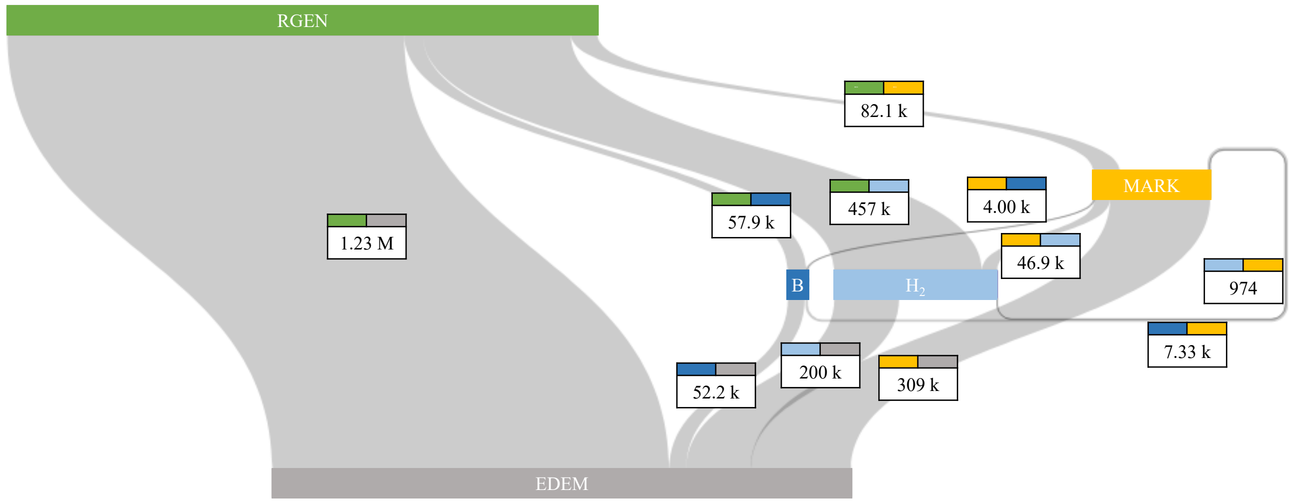
approach would not only lead to a considerable reduction of energy costs, but would also support the transition from conventional power plants to renewable power generation.

6.2. Outlook

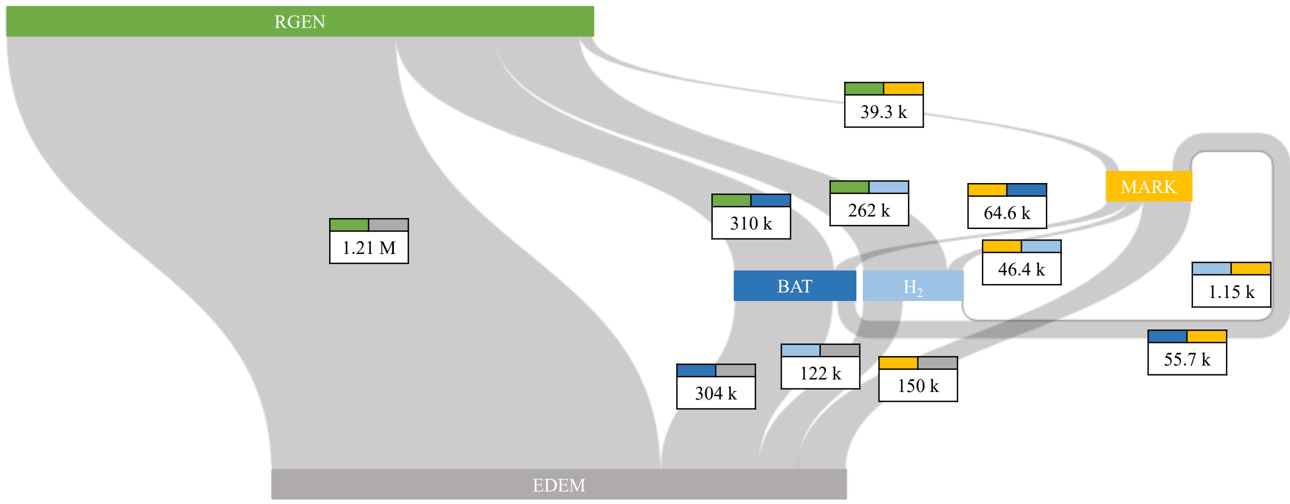
This thesis introduces a model for EAPP-BHS. More realistic technology characteristics, a combined ESS and the tracking of energy flows have been incorporated in the model. However, these model extensions also significantly increase computation time. Therefore, the computational efficiency remains a challenge despite the proposed two-stage optimization approach, which widely generates valid results. For a single weekly optimization run, the solution time was on average 14 minutes, which sums up to 12 hours optimization time for the long-term optimization stage. A few exceptional weeks took 30 minutes being responsible for explored outliers. Here, solver settings could be adapted to get more consistent results. The long-term optimization stage only took 2 minutes on average. Because of neglecting job scheduling and shift planning constraints, the second optimization stage is much faster than the first optimization stage, but relies on valid results of the more time critical first optimization stage. Therefore, an iterative optimization approach could have improved results. Here, data points from the yearly based optimization could serve as input for the initial fill and SOCs for a second optimization iteration. This was not part of the scope of this thesis. Hence, the identified outliers where not considered for concluding results derived from the conducted analyses steps.

The conducted analyses allowed to gain a better understanding of the potential and interdependencies of combined battery- and hydrogen-based energy storage systems for energy-aware production planning with renewable energy generation. The suitability of the combination of long-term and short-term energy storage systems to increase the utilization of on-site renewable energy generation and hedging against short- and mid-term energy price fluctuations was confirmed. An optimized ratio of battery to hydrogen storage capacity was identified. But, this ratio depends on the specific production case and prerequisites considered in this thesis, which are discussed in the following.

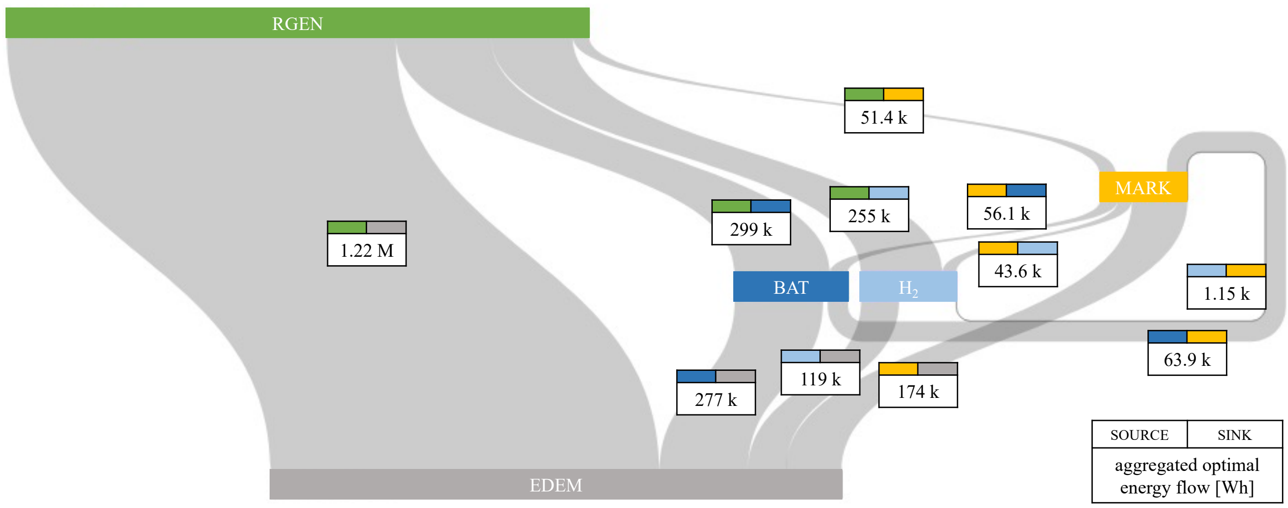
First, the assumptions presented in Section 4.1 and described input data for the numerical experiments in Section 5.1 create the framework for the derived solutions. The current state of technology is considered, but technological evolution may impact the managerial decisions in hybrid energy systems, thereby potentially requiring changes of input parameters to consider different technology specification scenarios. Additionally, the model is designed to find a cost-optimized solution given full information on renewable energy availability and price fluctuations. As a result RGEN-oriented production plans of the baseline scenario and considered test cases occur. In reality, such flexibility could only be achieved in fully automated workshops that are able



(a) Case 20: 400 MWh hydrogen storage, 100 kWh battery storage



(b) Case 28: 400 MWh hydrogen storage, 1200 kWh battery storage



(c) Case 25: 100 MWh hydrogen storage, 1200 kWh battery storage

Figure 7: Sankey diagrams of aggregated optimized energy flows.

to quickly respond to real-time operational decisions. Thus, the model is limited to decision support regarding the sizing of storage capacities and energy management, but does not qualify as a planning tool for future production planning. Moreover, the model is limited to one-stage production systems with parallel machines without warehousing. Second, the chosen renewable energy generation system (500 kWp wind onshore turbine and a 400 kWp PV) features a quite balanced energy generation output throughout the year. Potentially, systems relying on only one renewable energy source, nowadays mostly solar power, can benefit more from the combined storage system. Then long- and short-term storage could specialize even more on their scope of storage duration. Third, investments of the proposed ESS are not considered within the scope of this thesis. It remains questionable if energy saving potentials of combined ESS amortize in reasonable time. Fourth, the proposed model does not include a comprehensive consideration of energy consumption. Non-production processes included in the production company or waste heat utilization could be incorporated by more comprehensive models. For example, waste heat from the considered energy conversion by the assumed electrolyzer and fuel cell system could be used to satisfy local heating demands of the company's facilities. For the explored cost-optimized case approximately 180 MWh (60%) of the converted energy could not be used due to conversion losses mainly resulting in waste heat. This waste heat could be used to improve energy utilization and thus reduce total costs.

The following research directions can be derived for the future. First, forecasted technology scenarios could be applied to the model to investigate future potentials of combined ESS (cryogenic hydrogen storage, lithium-air batteries). Second, the presented cases can be generally extended in two dimensions. Larger battery storage capacities and smaller hydrogen storage capacities can be considered to investigate the model's behavior at approaching boundaries. Furthermore, different renewable power plant setups with more seasonally concentrated renewable energy generation and the model performance for different years could be tested. Third, more comprehensive energy management could be addressed by the consideration of non-production energy demand or waste heat utilization. And fourth, there is a gap for energy-aware production planning tools that incorporate energy management within micro-grid systems based on predictions for renewable energy generation or energy price developments to allow for improved decision support.

7. Summary

This thesis proposes a model for energy-aware production planning. The considered production system contains a production (maximum power demand: 383 kW), a wind turbine (capacity: 500 kWp), a photovoltaic system (capacity: 400 kWp), a battery (capacity: 100 - 1200 kWh) and hydrogen storage (capacity: 100 - 400 MWh) with an electrolyzer and fuel cell. Trading with the energy market is allowed in both directions for purchase and sale of electricity. Time-dependent feed-in tariffs and retail prices are considered for the German energy market in 2020. Renewable energy generation is based on average Germany-wide availability. The objective of this thesis is to investigate the utilization of combined battery- and hydrogen-based energy storage systems. To achieve this objective, Chapter 2 describes the characteristics of energy-aware production planning are described focusing on the European energy market, on-site renewable energy generation and storage technologies. Based on a literature review in Chapter 3, the missing consideration of combined short-term and long-term energy storage systems is identified. In Chapter 4, a formal mathematical model is developed as a mixed-integer linear program on the basis of the identified problem framework. Special features of the model compared to related research are the depiction of energy flows between the system components, especially in exchange with the considered combined energy storage system and the consideration of more realistic technology properties. Mathematical optimization of the model minimizes labor and energy costs. In Chapter 5, the model is applied to hypothetical numerical experiments. The influence of storage capacities on total costs, system autonomy, self-consumption, energy surplus and storage utilization rates is analyzed. For this purpose, different allocations of storage capacities are optimized using the model. The results show that the highest cost savings of 29.3% can be achieved with a renewable plant to battery to hydrogen storage capacity ratio of 3:4:1000 for the considered scenario. Based on the results from the numerical experiments, implications for a beneficial application of the proposed energy-aware production planning approach and for sizing storage capacities are derived in Chapter 6. Furthermore, the application of the model to other cases and possible extensions are suggested as fields for future research.

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