Energy-aware coordination of machine scheduling and support device recharging in production systems

Inaugural-Dissertation
zur Erlangung des akademischen Grades eines Doktors
der Wirtschafts- und Sozialwissenschaften
der Wirtschafts- und Sozialwissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

vorgelegt von
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Kiel, 2023

My work received funding for three years in form of a PhD scholarship by the Gesellschaft für Energie und Klimaschutz Schleswig-Holstein (EKSH).

Gedruckt mit der Genehmigung der Wirtschafts- und Sozialwissenschaftlichen Fakultät der Christian-Albrechts-Universität zu Kiel.

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Tag der mündlichen Prüfung:	04.07.2023

Table of Contents

List of Figures

List of Tables

List of Algorithms

Chapter 1

Synopsis

1.1 Opportunities and challenges of excessive renewable electricity generation

Electricity generation from renewable energy sources represents one option among others to achieve climate targets like the greenhouse gas neutrality that is supposed to be reached in Germany by 2045 (Bundesregierung 2022). With a focus on the electricity sector, a significant generation increase from renewable energy sources has become apparent over the last two decades. While in the year 2000, the renewable energy share of gross electricity consumption in Germany was just about 6 %, this share increased by the year 2021 to over 41 % (Umweltbundesamt 2022a). This share could have been even higher as Germany faced feed-in management actions which accounted for a loss of 5,818 GWh of renewable electricity in the year 2021. 95 % of this loss originates from wind energy as the renewable energy source most affected by feed-in management actions (Bundesnetzagentur 2021). Feed-in management actions are countermeasures to secure electricity grid stability by reducing or completely stopping renewable energy generation in times of peak generation. This means that considerably more renewable electricity could have been produced, but due to a lack of grid infrastructure, was unable to be fed into the grid. As a consequence, in times of feed-in management actions, excessive renewable energy is available that is not consumed but lost. To get an idea of the order of magnitude, the average German household consumes about 2,828 kWh of electricity per year (Statista 2022), meaning that the loss of 5,818 GWh could serve more than two million German households.

In 2021, Germany emitted a total of about 700 million tons of CO_2 (Umweltbundesamt 2022b). Assuming a potential use of excessive renewable energy, CO_2 savings of about 2.2 million tons CO_2 could have been achieved. This number is based on an emission factor of 0.38 kg CO_2 per kWh, which corresponds to the German electricity mix in the year 2021 (BDEW Bundesverband der Energie- und Wasserwirtschaft e.V. 2022). In addition to the loss of excessive renewable electricity, feed-in management actions are also accompanied by compensation claims amounting to around 807 million Euros in 2021, which are paid to operators of renewable energy plants that were unable to feed in their generated electricity (Bundesnetzagentur 2021).

Especially wind-abundant regions in northern Germany are affected by feed-in management actions and therefore exhibit high losses of excessive renewable electricity production. Combining the data of the *Marktstammdatenregister* (Bundesnetzagentur 2022), as the database of all power plants and power units in the German energy system, with the published feed-in management actions (Schleswig-Holstein Netz AG 2021), one can quantify the regional loss of excessive renewable electricity production at a district level. The heatmap in Figure 1.1 sketches this loss of renewable electricity production for the federal state of Schleswig-Holstein in 2021. The red color illustrates the annual loss of renewable electricity due to feed-in management actions of about 48 GWh per district. This figure reveals that particularly the northwestern wind-abundant region of Schleswig-Holstein is affected by substantial feed-in management actions.

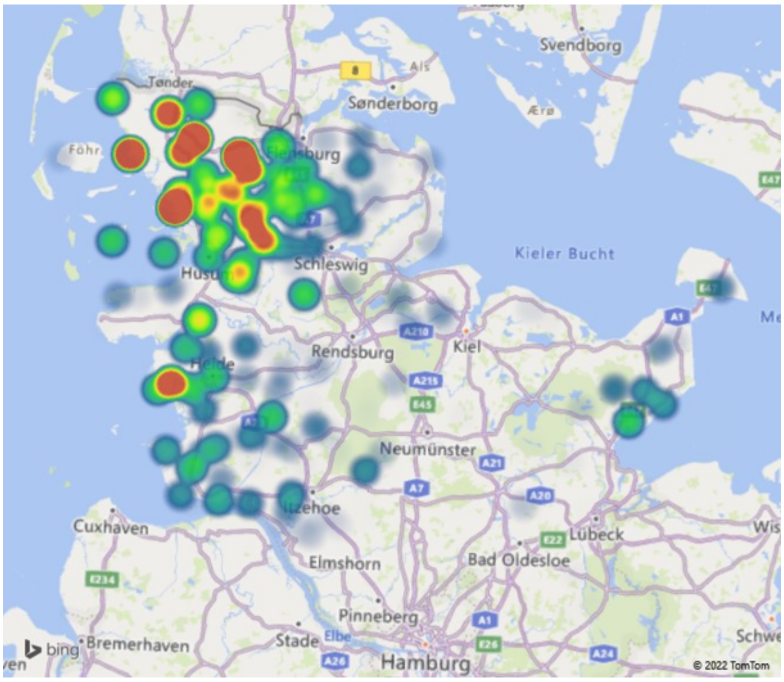

Figure 1.1: Loss of excessive renewable electricity in Schleswig-Holstein in 2021.

Feed-in management actions could be avoided if sufficient transmission capacity to distant consumers would be available in the power grid. However, extensions of the power grid infrastructure are both costly and time-consuming. One alternative approach to counteract feed-in management actions is to temporarily increase local electricity consumption. Hence, the higher electricity supply is synchronized with a corresponding demand, such that grid bottlenecks can be avoided as far as possible and feed-in management actions can be reduced. This creates an opportunity to relieve the power grid and extend the feed-in of renewably generated electricity.

With regard to German electricity consumption in the year 2021, the industry is the major sector of final electricity end use and accounts for approximately 44 % of the net electricity consumption (Destatis 2022). Trade, commerce, and services (27 %) as well as households (26 %), and transport (2 %) constitute the remaining 55 %. In this line of thought, the dissertation at hand comprises research on energy-aware manufacturing decision-making. A particular focus is on measures to counteract feed-in management actions and the loss of excessive renewable electricity through increased local industrial consumption in times of renewable generation peaks. The ENKO platform (Schleswig-Holstein Netz and ARGE Netz 2023) in Schleswig-Holstein provides an opportunity to connect local electricity consumers with grid operators to match possible electricity consumption flexibility with renewable energy generation in order to ensure grid stability. The approach presented in this dissertation uses an external signal based on the ENKO platform to guide production management decisions. It aims at synchronizing a company's internal energy consumption profile for the availability of renewable energy and, thus, achieving a more environmentally friendly production together with higher grid stability as a complement to the electricity grid stability-oriented ENKO platform.

The remainder of this cumulative dissertation is structured as follows. This chapter's ensuing four sections complete the synopsis. Section 1.2 describes the state of research by providing an overview of relevant literature and points out the research gap of interest. Section 1.3 gives an overview of each essay's research contribution and exhibits the essay's relations with one another. Section 1.4 briefly summarizes each essay's research in the form of an extended abstract. Section 1.5 concludes the synopsis by providing implications and outlining future research directions and opportunities. Following the synopsis in Chapter 1, the subsequent Chapters 2 to 5 are dedicated to the four essays. The dissertation concludes with an authorship contribution statement to each essay and a declaration of the originality and novelty of the submitted work.

1.2 State of research and research gap

Energy awareness in production environments gained increasing research attention over the last years. The increasing awareness of energy consumption and electricity costs has given rise to many novel decision-support-oriented publications as well as literature review articles. The following description of the state of research is therefore divided into two parts with regard to the individual essays' scope of this cumulative dissertation.

The dissertation at hand focuses on energy-aware research in industrial manufacturing environments, with an emphasis on decision-support models that are based on mathematical optimization. The literature reviews by Biel and Glock (2016) and Gahm et al. (2016) are most relevant in this context due to their focus on mathematical optimization and decision support models. Biel and Glock (2016) examine papers related to energy-efficiency in scheduling, capacity planning, and lot sizing, while Gahm et al. (2016) analyze scheduling models using a classification system that aggregates them at a higher level.

In the period from 2012 to 2021, several other literature review articles in the context of energy awareness can be found. Giret et al. (2015) focus on sustainable scheduling and categorize solution approaches in multi-objective environments. Garwood et al. (2018) review articles that incorporate energy considerations into production settings with a special emphasis on using simulation. Energy-oriented scheduling in combination with recent developments in machine learning is addressed by Narciso and Martins (2020). Along with the survey of publications on energy efficiency in the manufacturing system and assembly line context, Renna and Materi (2021) focus on articles that integrate renewable energy sources in manufacturing systems and point out publications that propose energy-saving strategies and policies. Literature on energy-oriented production planning is reviewed by Terbrack et al. (2021), aiming to derive core properties in energy-aware models within hierarchical production planning. There are further literature reviews that cope with energy awareness in a broader sense but do not meet the scope of energy-aware decision-support scheduling models in industrial production environments, see Duflou et al. (2012), Haapala et al. (2013), Weitzel and Glock (2018), Cui and Zhou (2018), Le Hesran et al. (2019), Cardoso et al. (2020), and Rathor and Saxena (2020).

Encouraging companies to adopt their production-related energy consumption to a targeted demand response event is typically referred to by the term *demand-side management* in the literature. A distinction can be made between *price-driven* and *event-driven demand response* approaches. Price-driven demand response means taking into account varying energy prices. Production-related energy consumption decisions are then adjusted to the energy price in order to smoothen electricity consumption patterns or reduce energy costs for instance. On the contrary, event-driven demand response aims to take special events into consideration, such as particularly high renewable energy generation. The subsequently described state of research on novel decision-support models will therefore differentiate price-driven and event-driven demand response approaches.

Price-driven demand response settings are considered in a vast number of publications. This literature is analyzed in detail in the first essay of this dissertation (see Chapter 2). The ensuing summary briefly describes those contributions that fall into this area and made a specific contribution to the field.

The following publications incorporate energy prices through time-of-use electricity (TOU) tariffs. In a single-machine production setting, Shrouf et al. (2014) minimize total energy consumption costs by adjusting the production schedule and Rubaiee and Yildirim (2019) minimize both completion time and energy costs. Che et al. (2017) study the impact of a time-of-use energy pricing system on scheduling parallel machines in order to minimize energy costs. Hemmati Far et al. (2019) study a flexible manufacturing environment including industrial robots and automated guided vehicles for material transport. The objective minimizes production and transport costs. With regard to unrelated parallel machines, Heydar et al. (2022) focus on energy-efficient scheduling and propose an approach from approximate dynamic programming. The objective is to minimize the makespan and total energy costs, including the cost of machine energy consumption in processing-, and idle-states. In a price-driven demand response setting Yun et al. (2022a) minimize production electricity costs with the additional consideration of material handling equipment recharging decisions.

Besides the widespread use of time-of-use electricity tariffs, there are other price-driven coordination mechanisms. Under a real-time pricing (RTP) scheme, Busse and Rieck (2022) emphasize a flow shop machine scheduling problem using electricity price forecasts. In a hybrid flow shop setting, Schulz et al. (2019) develop a multi-objective mixed-integer program that incorporates three objectives which aim to minimize the makespan, total energy costs, and peak power. In Yusta et al. (2010), the focus is on determining a production schedule that maximizes a company's profit, taking into account real-time energy prices that are updated at least hourly. The profit is calculated as the difference between sales income and the total production costs, including electricity costs. Lu et al. (2021) propose a neural network-based RTP prediction approach in a serial production line setting in order to minimize electricity costs and to meet production requirements. Yun et al. (2022b) develop a real-time demand response strategy to reduce electricity costs in a cyber-physical system-based manufacturing environment.

With regard to peak power costs, Schulz (2018) proposes an optimization model considering an objective function that minimizes energy consumption and peak power while accounting for volatile prices. In a capacitated flow shop environment, Masmoudi et al. (2017) minimize peak power as a part of the cost-oriented objective function. Hahn-Woernle and Günthner (2018) investigate how power-load management affects the efficiency of material-handling systems in automated warehouses, showing that limiting power consumption can prevent energy consumption peaks while slightly decreasing the throughput.

In the context of renewable energy generation, Subramanyam et al. (2020) create a two-stage mixed-integer model to reduce energy costs in a flow shop environment by incorporating on-site renewable energy sources. The first stage minimizes the yearly energy consumption while ensuring job throughput, while the second stage sizes wind turbines and solar panels to meet hourly electricity demand. In a flow shop scheduling problem with unpredictable wind power generation on the premise of the company and time-of-use electricity pricing, Biel et al. (2018) seek to minimize the weighted flow time and the expected energy costs. Zhang et al. (2018) focus on the optimal sizing of on-site energy generation and production planning in a manufacturing system under critical peak pricing conditions to minimize overall energy expenses.

In addition to renewable energy generation, the following publications additionally integrate energy storage. Karimi and Kwon (2021) analyze the influence of energy-oriented production scheduling with on-site solar energy generation in combination with energy storage in a battery on energy cost and makespan. Additionally, Wang et al. (2020) propose a stochastic two-stage multi-objective optimization model with time-of-use electricity prices considering on-site renewable energy generation in combination with an energy storage system. Materi et al. (2021) aim to reduce energy costs and CO_2 emissions by integrating a photovoltaic plant and battery storage into a production system.

With the previous state of research, it becomes apparent that energy-aware research in production planning almost exclusively applies price-driven demand response mechanisms. However, these prices reflect the market-wide availability of renewable energy and are unsuitable for indicating local renewable energy generation peaks. In order to counteract or avoid feed-in management actions at a regional district level, an event-driven demand response approach seems therefore more appropriate. Such an event-driven demand response could be achieved by integrating a feed-in management action forecast, like for example based on the previously mentioned ENKO platform, into an energy-aware machine scheduling model. From an energy-related point of view, also the integration of additional industrial energy consumers, such as devices for material handling or production factor supply seems reasonable and forms a further research gap. This dissertation fills these gaps by taking a comprehensive view of production equipment heterogeneity and proposing a flexible production coordination platform that can handle various equipment types' decision-making in an event-driven demand response setting. By doing so, this research is dedicated to the best possible linking of local renewable energy generation and production-related energy consumption. It aims at answering the question of how effective decentralized planning can be designed in order to optimize energy efficiency and CO_2 reduction in manufacturing. Furthermore, it analyzes how this concept can be evaluated within a simulation framework and what performance can be achieved in stochastic-dynamic situations using real production and environmental data.

1.3 Overview of thesis contributions

The thesis at hand is a cumulative dissertation where each of the following chapters represents a self-contained essay. Figure 1.2 gives an overview of the essays and indicates how they are interrelated with one another.

As a thematic introduction, Essay 1 provides a systematic literature review that surveys recent publications on energy-aware production decision support models. With this essay, a systematic classification of the state of the art of energy-aware research is provided. It then identifies current research streams, outlines promising future research potentials, and builds a profound basis for the research of Essays 2 to 4.

The common scope throughout Essays 2 to 4 is to propose and analyze an energy-aware production approach in an event-driven demand response setting. The essays investigate a coordination platform for decentral decision-making of heterogeneous manufacturing equipment and support devices under selected energy- and service-oriented goals. The manufacturing environment under consideration is inspired by a medium-sized metal processing company from northern Germany. Apart from established service-oriented goals, the novel environmental orientation aims to integrate a forecast for feed-in management actions in order to synchronize manufacturing and recharging activities with excessive renewable electricity generation. Briefly sketched, Essay 2 introduces the novel decision-making approach for machine scheduling and support device recharging. Derived from this, Essay 3 emphasizes support device decision-making and contrasts static recharging policies and optimization model-based charging decisions. Finally, Essay 4 compares machine scheduling in a job shop and flow shop production environment under

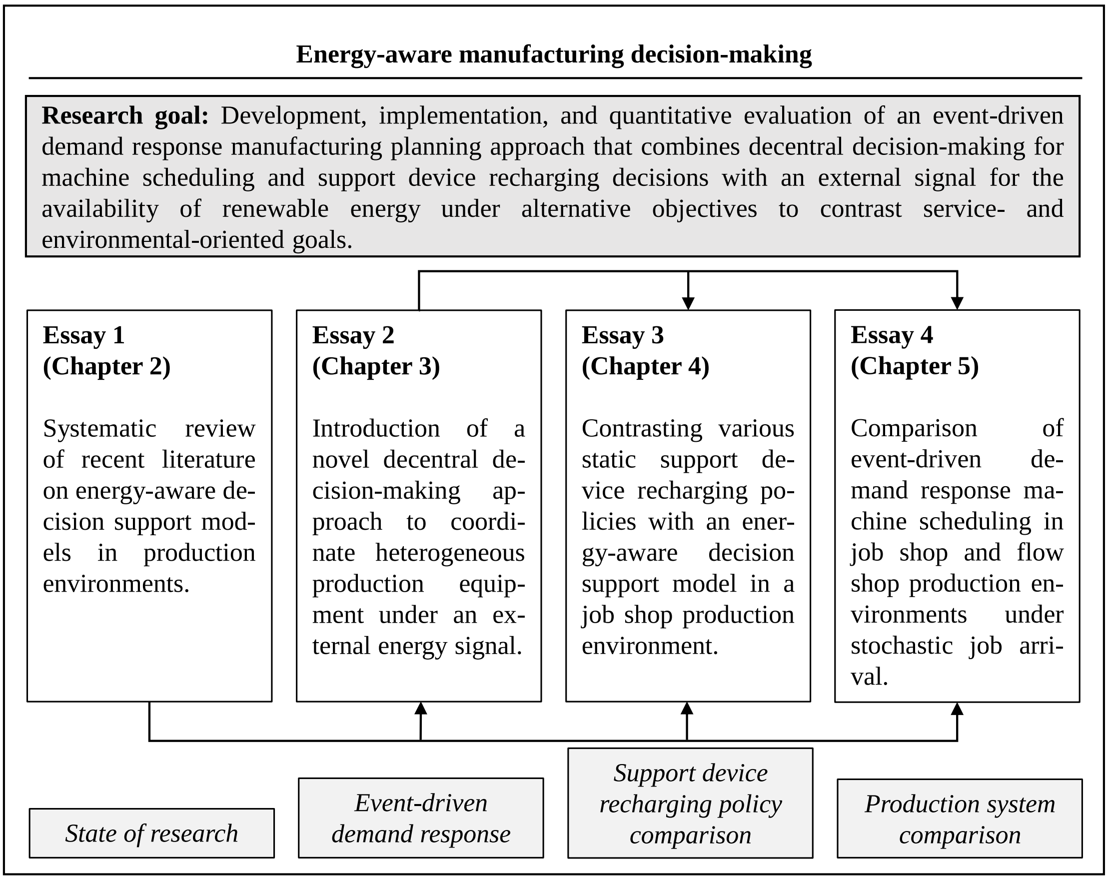

Figure 1.2: Research goal and procedure of this thesis.

stochastic job arrivals for both, service and environmental objectives.

Table 1.1 provides an overview of the four essays, their titles, author(s), year, and information about their publication status. The table also shows the ranking of the journals according to VHB-JOURQUAL3 (2021). The journals in which the essays are published or to which they have been submitted for possible publication are generally associated with the subject areas of production, industrial engineering, logistics, and operations research.

1.4 Extended abstracts

This section provides extended abstracts for each individual essay. In Subsection 1.4.1, the conducted systematic literature review is summarized. Subsection 1.4.2 will give a brief summary of an event-driven demand response-oriented approach to coordinate het-

Table 1.1: Overview of the essays belonging to this thesis.

Essay	Title	Author(s)	Year	Publication status	JQ3
Essay 1 (Chapter 2)	Energy-Aware Decision Support Models in Production Environments: A Systematic Literature Review	Kristian Bänsch, Jan Busse, Frank Meisel, Julia Rieck, Sebastian Scholz, Thomas Volling, Matthias G. Wichmann	2021	*Computers & Industrial Engineering*, 159: 107456.	B
Essay 2 (Chapter 3)	Coordination of heterogeneous production equipment under an external signal for sustainable energy	Sebastian Scholz, Frank Meisel	2022	*Journal of Cleaner Production*, 338: 130461.	B
Essay 3 (Chapter 4)	Decentral decision-making for energy-aware charging of intralogistics equipment	Sebastian Scholz	2023	*Logistics Research*, 16: 4.	C
Essay 4 (Chapter 5)	Energy-aware coordination of manufacturing equipment in flow shop and job shop production environments with stochastic job arrival	Sebastian Scholz, Frank Meisel	2023	Submitted to *Computers & Industrial Engineering*	B

erogeneous production equipment in terms of machines and support devices. Based on that, Subsection 1.4.3 will take up this approach and focus on support device recharging decisions. Finally, the extended abstract in Subsection 1.4.4 emphasizes machine processing in different production environments with stochastic job arrival.

1.4.1 Essay 1

Energy-Aware Decision Support Models in Production Environments: A Systematic Literature Review

Kristian Bänsch, Jan Busse, Frank Meisel, Julia Rieck, Sebastian Scholz, Thomas Volling, and Matthias G. Wichmann

As a starting point for this thesis, an introductory publication on the state of research on energy-aware production planning and control has been worked out (Bänsch et al. 2021). It is the result of the scientific cooperation of research groups from the Technical

University Berlin (TU Berlin), the University of Hildesheim, the Technical University Chemnitz (TU Chemnitz), and the Kiel University (Christian-Albrechts-Universität zu Kiel). This essay provides a well-founded introduction and a comprehensive overview of the research on energy-aware production planning up to that time.

The considerable energy consumption by industrial production has led to a large number of scientific publications that include environmental aspects and increased energy awareness into production management. Nowadays, approaches that promote sustainable energy sources like wind or solar energy, in combination with evolving technologies for on-site energy generation and energy storage, open up a variety of new opportunities to make industrial energy consumption more environmentally friendly. Building on previous scientific literature reviews, the research objective of this essay is to analyze and systematize recent publications from the years 2016 to 2020 with respect to environmentally-oriented mathematical decision support models.

In detail, nearly 200 relevant scientific articles are systematically analyzed in the areas of machine scheduling, lot-sizing, and other energy-intensive production processes. With the scope and the limits of the production system under investigation determined, established literature databases are searched with selected keywords. The classification of the literature is based on a developed ten-dimensional scheme, which is used to identify research areas that already received substantial scientific attention and areas that received less attention. Furthermore, it actively addresses topics of future research that are mentioned in previous literature review articles and shows to what extent these research gaps are covered by recent publications.

As a result of an initial quantitative evaluation of all identified articles, the survey deduces that the vast majority of publications consider classical energy supply through a power grid, while on-site generation, for example by wind turbines on the company premise, is hardly taken into account. In addition, the price of energy as a coordination mechanism for determining the best time for energy consumption is only discussed in about half of the articles. The essay works out that the distinction between price-driven and event-driven demand response approaches exists in theory but event-driven demand response approaches clearly lack consideration in the analyzed literature. In contrast to the energy price, event-driven demand response approaches aim to account for particular environmental conditions that can occur. As expected, nearly half of the articles under review deal with energy costs and energy consumption in the objective function. Another part considers objective functions with time components, such as minimizing the maximum tardiness of production orders or minimizing the completion time. Peak power and environmental objectives are less likely to be included in the models than assumed. The quantitative perspective of the survey is supplemented by a content analysis in order to highlight current developments and future research potentials. Likewise, the presentation of concrete case studies from practice makes it possible to point out specific industries in which energy-aware planning is frequently used. As a result of the content analysis, current research streams and future research potentials are identified.

In conclusion, this literature review focuses on articles that bring topics of sustainable energy generation, energy storage, and energy consumption into operational production planning problems. The essay provides a detailed analysis of current research streams and actively addresses and discusses future research of interest mentioned in earlier literature reviews. Furthermore, it presents in detail six research streams that can be identified in the recent literature. For each of these streams, it reveals those articles that already contribute to them so far and identifies associated fields for future research. Among the other areas, event-driven demand response environments state a field for future research. Through this, the survey contributes to the further development of energy-aware decision-making in production environments.

1.4.2 Essay 2

Energy-aware coordination of heterogeneous production equipment under an external signal for sustainable energy
Sebastian Scholz and Frank Meisel

This essay focuses on event-driven demand response (Scholz and Meisel 2022). While power grid operators face the challenge of ensuring grid stability, energy-intensive industrial manufacturing companies need to take care of their internal load management in order to avoid overloading the company's internal energy infrastructure and to prevent high energy costs. These two aspects are brought together in Essay 2. The novelty is to take into account heterogeneous manufacturing equipment with their individual decision-making processes. Machine production scheduling as well as charging decisions of inventory-oriented support devices, like electrified forklift trucks, are coordinated in such a way that a company's internal load management is included. Through this, increased local energy consumption during feed-in management action periods counteracts the loss of excessive renewable energy generation and ensures grid stability.

In this context, the company under consideration receives a forecast signal of necessary local feed-in management actions for upcoming periods. These feed-in management actions imply the occurrence of excessive renewable energy. The essay proposes two optimization models to take this forecast into consideration when making scheduling and charging decisions for heterogeneous production equipment. Lexicographically ordered objective functions minimize the total job tardiness, maximize energy consumption during feed-in management periods, and minimize the company's internal peak loads. Since it seems unrealistic to consider the heterogeneous consumers of a complex production system within a single, holistic mathematical decision model with regard to the different decision-makers of a company, a self-control concept in the form of a production coordination platform (PCP) for decentralized decision-making is developed. The PCP does not make decisions itself but calls the associated mathematical optimization models for the heterogenous manufacturing equipment units on demand. In this way, it coordinates the decisions and is able to account for a large number of heterogeneous production equipment types that are orchestrated with each other. The PCP continuously keeps track of the state of the entire production system, especially the load profile from the previously made production decisions, registers all decision-making requests, initiates the decision-making, and reports the decisions made to the relevant equipment. In this way, the platform incrementally creates a holistic operations plan for the production and support processes under consideration.

Computational experiments are based on a manufacturing system consisting of two heterogeneous production equipment types with two machines and two inventory-oriented support devices each. These experimental results show that the coordination platform makes equivalent decisions compared to a holistic and integrated optimization model that serves as a benchmark. It is also shown that the signal-driven coordination platform can achieve significant reductions in production-related CO_2 emissions. For this purpose, the role of various feed-in management scenarios is investigated to study the impact of different frequencies of feed-in management actions and the resulting environmental impact. Additionally, the conflict of objectives regarding peak load minimization on the one hand and counteracting feed-in management actions, on the other hand, becomes apparent.

Eventually, a newly proposed objective function for shifting production and charging processes into periods with feed-in management actions is shown to offer the possibility to minimize the loss of available renewable energy and to significantly reduce CO_2 emissions. The other two objective functions for minimizing the total job tardiness and minimizing peak loads show significantly higher energy consumption rates in periods without feed-in management actions and are consequently associated with higher CO_2 emissions. Furthermore, sensitivity analyses of crucial influencing parameters show how different degrees of information availability affect the performance of the PCP.

1.4.3 Essay 3

Decentral decision-making for energy-aware charging of intralogistics equipment

Sebastian Scholz

In addition to machines that process jobs in an industrial company, corresponding intralogistics-related support devices are another significant energy consumer (Scholz 2023). They are responsible, for example, for supplying materials to the machines by means of electric forklifts. However, the consideration of electricity-intensive intralogistics has hardly been taken into account in research on energy-aware production planning and builds this essay's research scope. The coordination platform, introduced in Essay 2, is therefore adapted and extended to replicate established static charging policies in contrast to optimization-model-based decision-making.

Principally, charging policies are divided into periodic charging procedures (t,q-policy, t,S-policy) and continuous procedures (s,q-policy, s,S-policy). In the case of periodic charging procedures, charging takes place at specific and fixed time intervals t, whereby either a fixed amount q is charged or charging is conducted until an order-up-to level S is reached. In contrast, in continuous charging procedures, charging is initiated when the state of charge falls below a defined threshold, the order point s. At this point, either a fixed amount q is charged or charging goes up to the order-up-to level S. In a simulation study based on real production data of a metal-processing company from Schleswig-Holstein, the role of intralogistics charging decisions is analyzed. In this simulation, four static charging policies are compared with each other and to an optimization model specially developed for the charging decisions of intralogistics devices.

In general, the static charging policies' order point s, order-up-to level S, and charge amount q are important parameters but assumed to be given due to intralogistics equipment's technical restrictions. Apart from this, the charge interval t is within the scope of a company's decision-making authority and influences the production scheduling segment. This is because sufficient inventory of intralogistics is required to maintain machine production. The mandatory parameterization for the subsequent computational experiments defines the charging interval t. This guarantees adequate intralogistics inventory to achieve the highest possible job processing rate when using a static charging policy. It can be stated that all static charging policies reveal electricity consumption in both types of periods, with and without feed-in management actions, since they strictly follow the given time regime. Only the optimization model approach is able to entirely shift intralogistics charging decisions into periods with feed-in management actions. In addition to the comparison of the five different charging policies, the impact of different intralogistics demand durations is analyzed. By varying the length over which the demand is applied, the simulation study also investigates changes in the demand for intralogistics fulfillment. The results state that the job processing rate decreases with an increasing demand length. Additionally, the analysis contrasts a forklift selection by highest inventory to a consistent forklift selection mechanism. The computational experiments show that the general findings do not differ for these alternative forklift deployment strategies.

In conclusion, only the optimization approach reasonably anticipates excessive renewable electricity generation during periods of feed-in management actions. This gives the decision makers of a company the opportunity to reduce the loss of excessive renewable electricity generation and thereby contribute to a reduction of CO_2 emissions.

1.4.4 Essay 4

Energy-aware coordination of manufacturing equipment in flow shop and job shop production environments with stochastic job arrival
Sebastian Scholz and Frank Meisel

The concept of energy-aware coordination of heterogeneous manufacturing equipment was initially investigated in Essay 2 based on a production environment with a predetermined job set and without machine precedence relations. In that paper, it was only necessary that each job is processed on each machine, regardless of the machine order. The research objective of Essay 4 is to compare in more detail job shop and flow shop production environments also accounting for stochastic job arrival (Scholz and Meisel 2023). In this setting, production jobs are unknown in advance and arrive in the course of time.

More precisely, each job now persists of a set of operations that have to be processed by several machines and in a given machine routing. The study makes use of the basic decentralized decision-making platform concept from Essay 2 to coordinate different types of production and intralogistics equipment. By accounting for exponentially distributed job inter-arrival times it is capable to consider stochastic job arrivals. Different job arrival scenarios are represented by varying job inter-arrival times, which range from a starving up to an overloaded production system. In this context, a starving production system is represented by a relatively low number of job arrivals and a corresponding low machine utilization rate. An overloaded production system is characterized by a high number of job arrivals and is accompanied by a high machine utilization rate. This variation enables the analysis of the production coordination platform's performance under various job arrival conditions. In a simulation based on real-world data from a metal-processing mid-size company from northern Germany, the essay examines the impact of different production environments on PCP performance indicators. Thereby, jobs exhibit consistent operation sequences in a flow shop setting due to the fabrication of homogeneous products and, hence, result in identical machine sequences, whereas the job shop environment is characterized by job-specific machine and operation sequences focusing on the fabrication of heterogeneous products.

The study can demonstrate that the PCP is capable to handle stochastic job arrivals in both production environments and that a too-high job release rate exerts a negative impact on the overall job processing rate. Thereby, it is shown that the released job amount per scheduling run is an important parameter to keep production at a preferable level and strongly influences the PCP's performance. It can be seen that the flow shop processing rate is principally lower compared to the job shop setting for an identical job inter-arrival time. This is somewhat unexpected but due to the higher number of operations per job, as processing necessarily takes place on all machines for each job in the flow shop environment. Furthermore, the paper introduces and investigates operation-specific due dates compared to job-specific due dates in order to reduce tardiness in the rolling horizon planning of the decentral decision-making process. As a benchmark, all machines are provided with the final job due dates, which results in the highest total tardiness. With the *equal division*, an operation-specific due date is introduced that is calculated for each machine operation individually. There, the processing time window between the arrival date and the due date is equally shared among all operations and each machine receives an individual due date with regard to the operation order. Furthermore, the *weighted division* takes differences in the processing times of operations into account, such that a longer processing operation receives a larger share of the processing time window. The computational results demonstrate that the introduced operation-specific due dates are beneficial as they reduce the total tardiness in a job shop environment as well as a flow shop environment under various objective combinations.

In conclusion, the essay reveals that the proposed PCP is capable to handle complex jobs with stochastic job arrivals and given machine precedence relations in both job shop and flow shop environments. The energy-aware orientation is still capable to counteract excessive renewable energy generation in these settings, even though it comes at the expense of high job tardiness values.

1.5 Implications and future research

The synopsis concludes with implications derived from the essays and a brief description of promising future research directions.

A clear implication of this work is that event-driven demand response in production environments constitutes a promising and little-researched area of interest. This comes into effect, especially in the context of the energy transition with increasing renewable energy integration. The thesis lays the foundation for further investigations by proposing a first optimization model-based approach to counteract feed-in management actions. Essay 1 outlines that decision-support models in production environments are subject of particular attention over the last few years. At the same time, current research gaps as well as future research potentials are identified and indicate that event-driven demand response approaches lack consideration in the literature. Considering an integrated environmental perspective, it appears logical to follow a combined perspective of energy-intensive intralogistics in combination with production-related job scheduling. The results of Essay 2 suggest that decentral decision-making for heterogeneous production equipment in an event-driven demand response environment can become an effective production planning concept to cope with the availability of excessive renewable energy. The integration of production scheduling with intralogistics charging decision-making appears as a holistic way to account for a company's most relevant energy consumers. Essay 3 indicates that the little-studied research field of intralogistics recharging decisions also contributes to substantially counteracting feed-in management actions. Finally, Essay 4 has shown that the proposed production coordination approach is capable to handle stochastic job arrivals with complex job structures and machine precedence relations in different production environments. This essay opens up research paths for alternative job characteristics, e.g., preemptive production environments.

An important direction for future research relates to the development of adequate incentive systems, that motivate companies to adapt their manufacturing electricity consumption to the occurrence of feed-in management actions beyond the environmental aspect. In this context, Essay 2 suggests that a peak load determination only in times without feed-in management actions would constitute a monetary incentive for companies to increase electricity production in times of excessive renewable electricity generation.

Another direction for future research puts emphasis on the coordination mechanisms of demand response schemes. As price-driven demand response approaches are predominant in the literature compared to the rarely considered event-driven demand response, further investigations on event-driven concepts or suitable combinations of both are desirable. For this, Essays 2, 3, and 4, have contributed to a better understanding of event-driven demand response strategies. Further extensions of the proposed approach, in the sense of negotiations of types of equipment that participate on the platform, are plausible.

A further direction for future research aims at a district-based analysis of feed-in management actions. Figure 1.1 already revealed fundamental regional differences regarding feed-in management actions and the resulting loss due to excessive renewable electricity. In this context, a regional and district-based analysis of feed-in management actions could reveal beneficial insights for managers as well as grid operators to conduct operational changes regarding the duration or time of the day of feed-in management actions or to regionally classify necessary feed-in management actions. Such an analysis could serve as a helpful basis for practitioners to be able to assess feed-in management actions in their company site-related district.

Further, implications for practitioners are that companies can clearly contribute to reducing feed-in management actions by adjusting their electricity consumption. However, the conflicting objectives of service- and energy-oriented goals must be considered here to trade off customer satisfaction and environmental orientation. An economic and political implication is that there is a need to develop incentive mechanisms to make it attractive for manufacturing companies to adapt their operations to the availability of renewable energy.

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Chapter 2

Energy-Aware Decision Support Models in Production Environments: A Systematic Literature Review

Publication status Published in 2021: *Computers & Industrial Engineering* 159: 107456. https://doi.org/10.1016/j.cie.2021.107456

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Abstract The substantial amount of energy consumed through industrial production has given rise to a large number of research papers that incorporate environmental aspects and increased energy-awareness into production management. Nowadays, initiatives that push sustainable energy sources like wind and solar power together with new technologies for on-site power generation and energy storage open up a multitude of new options for making industrial energy consumption more environmental friendly. With this paper, we review the recent literature that attempts to reflect these options within industrial decision support models. We conduct a systematic literature review that identifies relevant papers from fields like machine scheduling, lot sizing, and other energy-intensive processes. For classifying the literature, a multi-dimensional scheme is developed that helps identifying areas that already received substantial scientific interest and areas that are not yet well understood. To this end, we actively address areas of future research that were mentioned in earlier review papers and show to what extent these gaps where closed by recent publications. Through this, we observe substantial progress with regard to various aspects such as pushing system boundaries, coming up with advanced conceptual approaches, and striving for more practical relevance. Nevertheless, there remains a substantial number of issues that have not yet been approached thoroughly.

Keywords Energy-awareness, production planning, scheduling, lot sizing, literature review, decision support models

2.1 Introduction

According to the U. S. Energy Information Administration (2016), about 54 % of the total delivered energy worldwide is consumed by the industry sector. In the context of production planning and scheduling, particularly energy-intensive manufacturing processes (e.g., in the iron and steel, paper, or chemical industry) are of major interest. Here, a considerable amount of energy is required for running the machines, aiming at transforming input (i.e., raw materials) into desired output (i.e., final products). With an expected average growth rate of 1.3 % per year during the period from 2012 to 2040, electricity is the second fastest growing energy source right after natural gas (U. S. Energy Information Administration 2016), indicating the continuously increasing demand for industrial applications. Looking at China as an example, about 50 % of the total produced electricity is consumed by the manufacturing industry (Liu et al. 2014). In many industries, electricity costs make up by far the largest proportion of production-related energy costs (Wichmann et al. 2019a).

Within the last couple of years, the increasing awareness of energy demand and electricity costs, respectively, has given rise to a large number of publications in manufacturing environments, which resulted in a multitude of review papers. Early review articles tried to structure the field, delivering a high level description with a focus on concepts and technologies (Duflou et al. 2012, Haapala et al. 2013). With more and more articles being published, subsequent reviews dealt with specific sub-aspects of energy-aware production planning. Giret et al. (2015) examine sustainable scheduling in a broader sense, focusing on categorising solution approaches in multi-objective environments. Cui and Zhou (2018) address power load scheduling in demand response programs, but scheduling is not discussed in detail. Garwood et al. (2018) review articles that use simulation to include energy aspects into production settings. Weitzel and Glock (2018) structure methods for the planning of electrical storage systems, while industrial applications are outside their scope of investigation. Le Hesran et al. (2019) specifically consider articles that deal with waste minimisation, where energy is integrated as a side aspect. Cardoso et al. (2020) study demand response programs, including only companies in the service sector. Narciso and Martins (2020) structure the new advances of machine learning into energy-oriented scheduling applications. Finally, Rathor and Saxena (2020) take up the topic of smart grid energy management, without explicitly covering industrial aspects.

The main focus of the systematic literature review conduced in this paper is on energy-related research in manufacturing environments, but with a strong focus on *decision support models* based on mathematical optimisation. The approach of the review at hand is closely related to the earlier surveys of Biel and Glock (2016b) as well as of Gahm et al. (2016). Following the above mentioned surveys, the literature search only encompasses decision support models that are based on mathematical optimisation. Other approaches like statistical investigations or models based on artificial intelligence are beyond the scope of this literature review and form a basis for further independent studies. In Biel and Glock (2016b), papers linked to energy-efficient scheduling, capacity planning, and lot sizing are considered, and in Gahm et al. (2016), articles are discussed that focus on the analysis of scheduling models at an aggregated classification level. In this line of thought, the paper at hand combines both approaches and can be further regarded as an essential update and extension of the aforementioned overviews. On the one hand, our literature search covers a wide range of possible *energy-related challenges* in manufacturing (e.g., scheduling, sequencing, lot sizing, multiple modes, and multiple objectives). In order to structure the field, we provide an extensive classification scheme that allows for comprehensive comparisons and, in particular, takes up recent developments in the energy sector. On the other hand, we specifically look into *open research areas* that have already been identified by Gahm et al. (2016) as well as Biel and Glock (2016b). Thereby, we discuss articles that address or fill open areas. Such open areas of research can be assigned to the main categories system boundary, conceptualisation, and practical relevance. Here, 'system boundary' refers to approaches that deal, e.g., with on-site generation and storage or with increasing the efficiency of upstream processes of energy supply. The category ‘conceptualisation’ includes, e.g., stochastic dynamic environmental approaches or approaches of machine learning. Finally, the ‘practical relevance’ contains, e.g., realistic model formulations or real-life case studies. We take up these categories in the later part of this paper and show what other papers contribute to these less investigated areas of research. In addition, we identify and present further innovative streams of research, where we point out remaining blind spots that might be fruitful areas for future research.

The remainder of this paper is organised as follows. In Section 2.2, we describe our systematic literature search process and the derived scheme for classifying the relevant articles. In Section 2.3, we provide a brief quantitative analysis of the research field, which is followed by a structured and detailed discussion of recent research in the various areas of machine scheduling and lot sizing in Section 2.4. In Section 2.5, we explicitly discuss how recent research contributes to open research questions mentioned in previous survey papers. Moreover, we identify and describe upcoming streams of recent developments and we outline topics for future research. Finally, Section 2.6 concludes the paper.

2.2 Literature search

In order to describe our literature search, we first present the search process methodology in Section 2.2.1 together with a brief overview of the number of articles found in different journals. We then present a classification scheme in Section 2.2.2 that is used afterwards for structuring the field of research.

2.2.1 Scope and literature search process

Figure 2.1 illustrates the generic framework which we use to define the scope of our literature review. The framework’s core element relies on the production environment within a manufacturing company (‘system boundary’), including (but not limited to) machines and supporting processes (e.g., transportation) that require electricity to perform or to assist the production. These ‘energy-intensive processes’ typically obtain their required amount of electricity from the grid (‘energy market’). Due to the continuous expansion of renewable energies such as wind and solar power along with their uncertain generation capacities, a rising imbalance of electricity supply and demand can be observed. As a result, energy suppliers encourage companies to adapt their production processes to the power generation by introducing time-varying electricity prices such as time-of-use

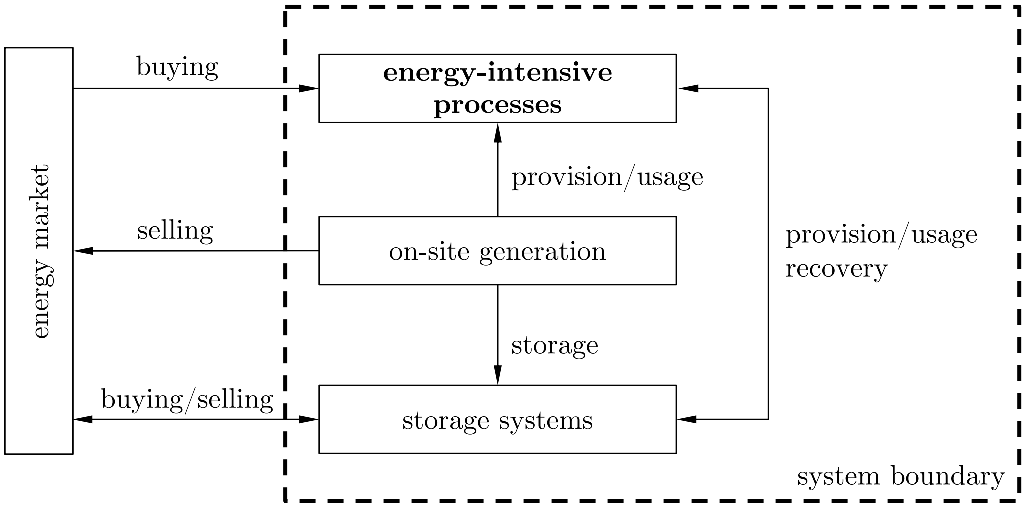


Figure 2.1: Boundaries and scope of considered system.

(TOU) tariffs. Moreover, electricity may also be purchased on spot markets (e.g., day-ahead markets), where supply contracts are being fulfilled in the very short-term and on an hourly basis (real-time pricing, RTP). In both cases, physical delivery of electricity is carried out through an external grid. By contrast, 'on-site generation' enables manufacturing companies to reduce their dependence on external energy supply by installing on-site power generation devices such as wind turbines or combined heat and power plants. In combination with energy 'storage systems', manufacturing companies gain a high level of flexibility, since generated electricity may be stored for later usage. In order to make optimal economic use of a storage system, companies can also buy electricity and fill the storage when market prices are low or they can sell stored electricity when market prices are sufficiently high. Additionally, waste heat from energy-intensive production processes may also be recovered by storage systems for later provision. Particularly, the consideration of on-site generation and energy storage systems has not been covered in the previous review articles by Biel and Glock (2016b) and Gahm et al. (2016). However, current research such as Liu (2016), Ruiz Duarte et al. (2020), Fazli Khalaf and Wang (2018), or Wichmann et al. (2019b) clearly point out that these issues need to be incorporated into decision making.

Based on the methodology proposed by Vom Brocke et al. (2009), Figure 2.2 visualises our literature search process and the development of a classification scheme. A key component of a survey is the definition of its literature research scope (step 1) as shown in Figure 2.1. The entry into the iterative process (steps 2 to 5 are passed several times)

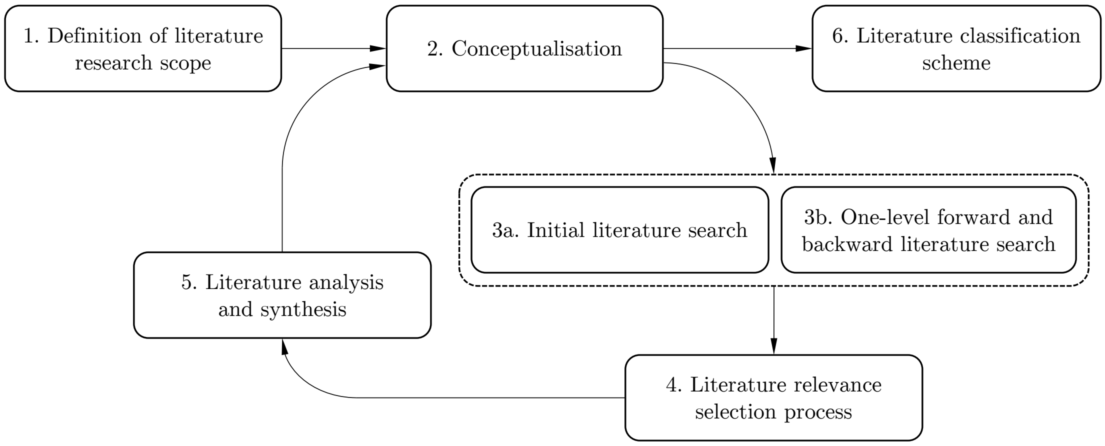


Figure 2.2: Literature search process (Vom Brocke et al. 2009).

is given by the initial conceptualisation (step 2). After having specified the topic of interest in principle, we have defined three categories of keywords; see Table 2.1. The first keyword category is related to production planning approaches, the second category is related to energy, and the third category corresponds to optimisation models. To account for any relevant article, the keywords are formulated in a generic manner. We combine all keywords to generate a final list of keyword combinations. Please note that the third category is extended to nine keywords for the actual search, as we incorporate American and British English.

Table 2.1: Overview of search keywords.

Keyword category 1	Keyword category 2	Keyword category 3
– Production planning	– Energy	– Mathematical model
– Scheduling	– Electricity	– Mathematical optimisation
– Manufacturing system	– Load management	– Optimisation model
– Industrial system	– Demand side management	– Optimisation problem
– Lot sizing		– Heuristic
		– MIP model

The first literature search (step 3a) is conducted using the scholarly database Scopus which contains peer-reviewed articles. During the search, care was taken to ensure that keyword combinations were included in the title, abstract, or list of keywords and that the articles were published from 2016 up to 2020. Assuming that high quality research is published in academic journals, we limit ourselves to journals and especially to those in the field of management-oriented operations research. The literature relevance selection process (step 4) analyses each article's relevance by checking its title, abstract, keywords, and main text. To classify an article as relevant, it must fulfil the following criteria: The first criterion arises from the third keyword category that reveals the decision support focus comprising mathematical optimisation models. The second criterion demonstrates an exclusive inclusion of papers that address planning problems within a manufacturing environment. The third criterion shows the strong focus on energy. Any optimisation models and objectives must explicitly address energy concerns. In step 5, the literature analysis and synthesis of the articles chosen so far is performed by analysing the entire articles' contents. With the resulting information, the articles can be incorporated into the initial conceptualisation phase (step 2). Moreover, the current literature classification scheme (step 6) can now be established with a useful set of dimensions and attributes (cf. Subsection 2.2.2).

After a first run through steps 2 to 5, we validated and expanded the original conceptualisation by performing a one-level forward as well as a one-level backward search (step 3b) in order to identify relevant articles that cite any of the so-far selected articles. Afterwards, the steps were repeated and, where necessary, the dimensions and categories of the derived literature classification scheme were adjusted. Eventually, we obtained our final classification scheme (step 6) that is described in detail in Subsection 2.2.2.

Within our search process, we identified a total of 192 relevant articles incorporating energy-awareness in production environments. Over time, an increasing amount of publications developed. While 30 articles were published in both 2016 and 2017, 39 articles were published in 2018, 65 in 2019, and 28 in early 2020. The continuously increasing number of articles published in the last years impressively underlines the need for a *systematic literature review* that structures the existing research and identifies relevant research gaps. Figure 2.3 shows the number of articles in those management-oriented operations research journals that published at least four relevant articles. Table 2.2 lists those journals that published three or less articles each, which make up the 37 articles in category 'others' shown in Figure 2.3. Please note that approximately 60 % of the articles appeared in only four journals out of a total of 32.

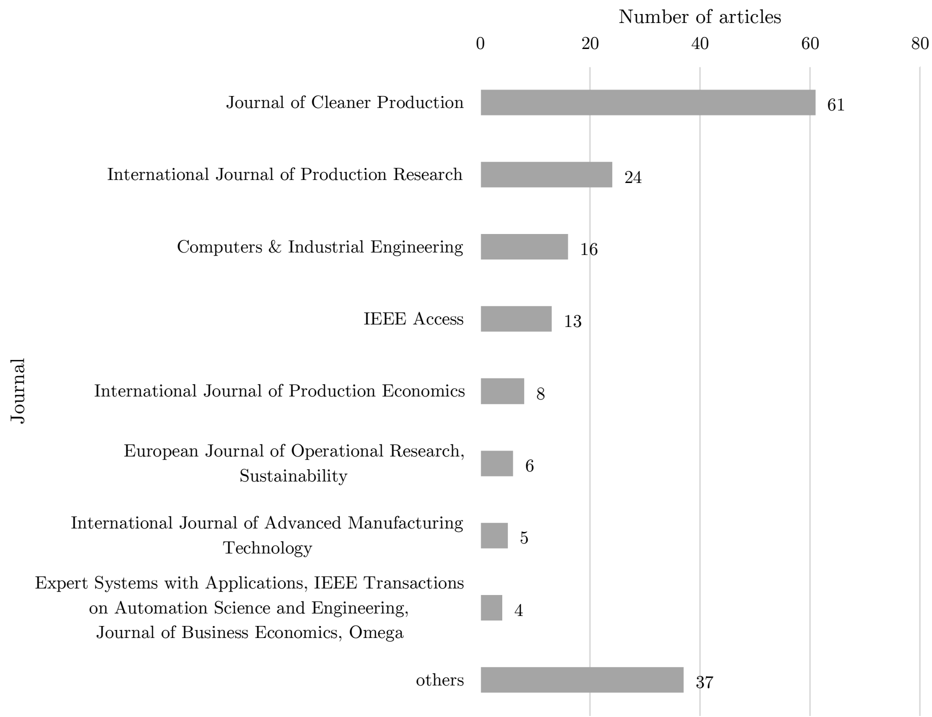


Figure 2.3: Number of articles per journal with energy-awareness in production environments.

Table 2.2: Journals with three or less relevant articles.

Journal	Articles per journal
Annals of Operations Research; Applied Energy; Computers & Chemical Engineering; Computers & Operations Research; Energy; Journal of the Operational Research Society;	3
Energies; Engineering Optimization; IEEE Transactions on Engineering Management; IEEE Transactions on Systems, Man, and Cybernetics: Systems;	2
Algorithms; Computers in Industry; Decision Support Systems; EURO Journal on Computational Optimization; IEEE Transactions on Industrial Informatics; International Journal of Energy Research; International Journal of Energy Sector Management; International Journal of Operational Research; Journal of Industrial Engineering and Management Studies; Naval Research Logistics; Production and Operations Management;	1

2.2.2 Literature classification scheme

In order to structure the relevant literature, we propose a ten-dimensional *classification scheme* that was derived from analysing previous literature reviews (Gahm et al. 2016, Biel and Glock 2016b) and the papers that were found through the search process. The scheme is shown in Figure 2.4. The first three dimensions A–C classify the articles in terms of their energy related scope. In particular, a distinction is made between energy supply, energy demand, and energy storage. The further seven dimensions D–J refer to the modelling approach, taking into account the objective criterion, the system of objectives, the manufacturing model, the mode characteristics, the planning horizon, the model type, and the proposed solution method. Within each dimension, we further define attributes and categories (groups of attributes).

The *energy supply* (dimension A) contains two categories ‘generation’ and the underlying ‘coordination mechanism’. The energy generation can either be realised by the grid (off-site), by an adjustable on-site facility (e.g., combined heat and power, incineration plant), or by a non-adjustable on-site facility (e.g., solar, wind), where the terms off-site and on-site refer to the location of generation plants. Adjustable facilities are operated according to demand, whereas the operation of non-adjustable facilities depends on the temporal availability of external factors such as wind or sun. The coordination mechanism takes into account measures to determine the timing of energy consumption (demand response). In principle, previous research revealed that a distinction can be made between price-driven and event-driven demand response (Gahm et al. 2016). Particularly, the demand side management in companies encourages consumers to adopt a targeted demand response, where consumption patterns are changed either in response to electricity price variations (e.g., TOU, critical peak pricing, RTP, and load curve penalties) or in response to specific trigger events, e.g., extreme weather conditions (Sun and Li 2014). Due to the fact that our literature search solely revealed price-driven demand response, we mention this differentiation only for the sake of completeness, but it is not considered in the rest of this paper.

The actual *energy demand* (dimension B) distinguishes between ‘processing energy demand’ and ‘non-processing energy demand’. Processing energy demand accounts for the energy consumed to operate manufacturing machines that are directly in relation with a company’s value added. By contrast, non-processing energy demand reflects activities not directly connected to value adding (e.g., machine idle, machine setup, material handling, and storage).

Looking at *energy storage* types (dimension C), we distinguish between three cate-

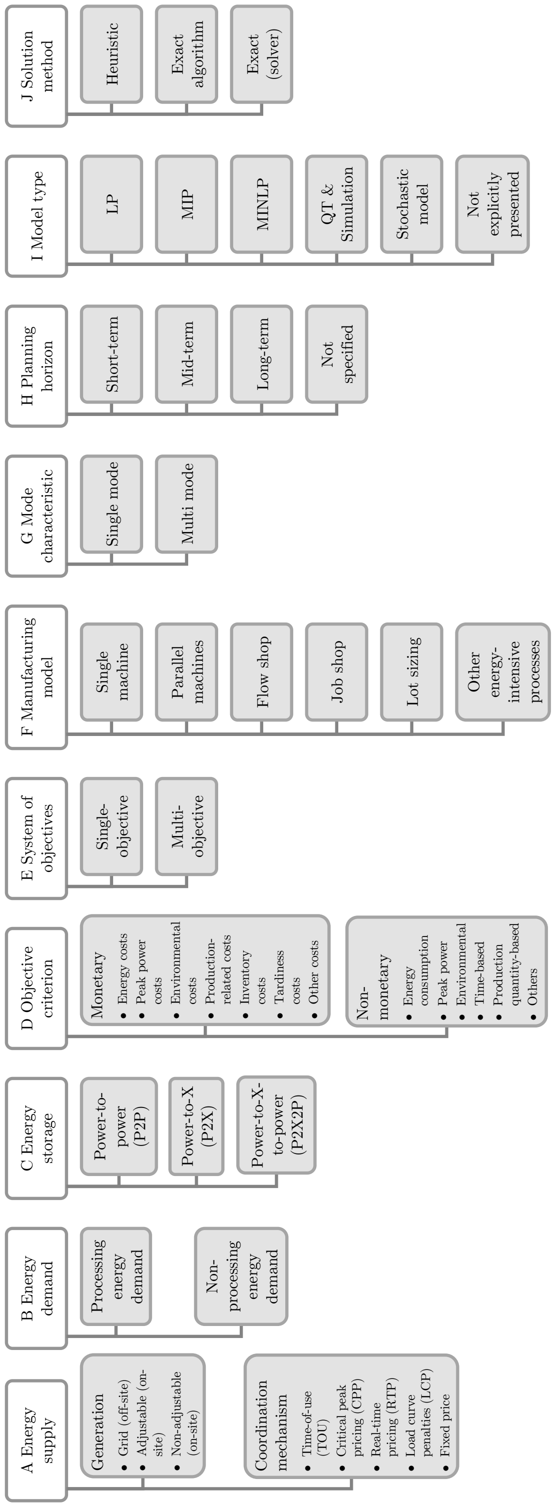


Figure 2.4: Literature classification scheme.

gories to capture various possibilities for energy conversion and reconversion. 'Power-to-power' (P2P) indicates storage types where no conversion takes place, since electricity is fed into the storage facility and electricity is also retrieved from it. 'Power-to-X' (P2X) refers to storage types that convert input electricity into a different output type of energy (e.g., Power-to-Gas, Power-to-Heat). Finally, 'Power-to-X-to-power' (P2X2P) storage types even account for reconversion when input electricity is fed, converted (e.g., into hydrogen), and stored in the storage facility and later reconverted back into electricity.

Regarding the modelling approach, the *objective criterion* (dimension D) shows the formulation of objective functions and differentiates between two categories: 'monetary' and 'non-monetary' objectives. The monetary category includes the minimisation of costs related to energy consumption, peak power, environmental (e.g., CO_2 emission costs), production-related, inventory, tardiness, and other. The non-monetary category considers the minimisation of energy consumption and peak power as well as the optimisation of environmental (e.g., carbon emission), time-based (e.g., makespan, tardiness), production quantity-based, and other non-monetary performance measures.

The *system of objectives* (dimension E) distinguishes between 'single-' and 'multi-objectives'. While single-objective formulations solely exhibit variables referring to a single dimensional unit (e.g., costs), multi-objective formulations take various dimensional units (e.g., costs and emissions) into account (Pinedo 2016).

The underlying *manufacturing model* (dimension F) differentiates five established manufacturing environments ('single machine', 'parallel machine', 'flow shop', 'job shop', 'lot sizing'). A sixth attribute 'other' is added as a collective term for further energy-intensive processes'.

The *mode characteristic* (dimension G) reflects the machine respectively job execution modes. A 'single-mode' characteristic is present when a job can only be processed in a single execution mode going along with a given processing time and energy consumption. We also assume the single-mode characteristic in case of parallel machines with identical processing times. On the contrary, a 'multi-mode' characteristic stands for various execution modes (e.g., several machine speeds or heterogeneous machines) being available for processing a job.

A time perspective is included by the *planning horizon* (dimension H). Here, 'short-term' ($< 24\,\text{h}$), 'mid-term' ($> 24\,\text{h}$), and 'long-term' (weeks/months) planning horizons are distinguished, which is useful especially when dealing with time-varying electricity prices (Windler et al. 2019). The additional attribute 'not specified' has been introduced for papers with a generic time perspective that do not refer to a particular time horizon.

The *model type* (dimension I) used in the research is either linear programming

('LP'), mixed-integer linear programming ('MIP'), mixed-integer non-linear programming ('MINLP'), queueing theory ('QT') and simulation or 'stochastic models'. The attribute 'not explicitly presented' accounts for all articles that do not present an explicit mathematical model formulation.

Finally, *solution method* (dimension J) indicates the type of method that is proposed in a paper for solving the optimisation problem. This can be a 'heuristic' (e.g., a genetic algorithm) or an 'exact algorithm' (e.g., a branch-and-bound). 'Exact (Solver)' refers to papers that propose the use of a standard solver (e.g., CPLEX or Gurobi) for obtaining a solution for the problem under investigation.

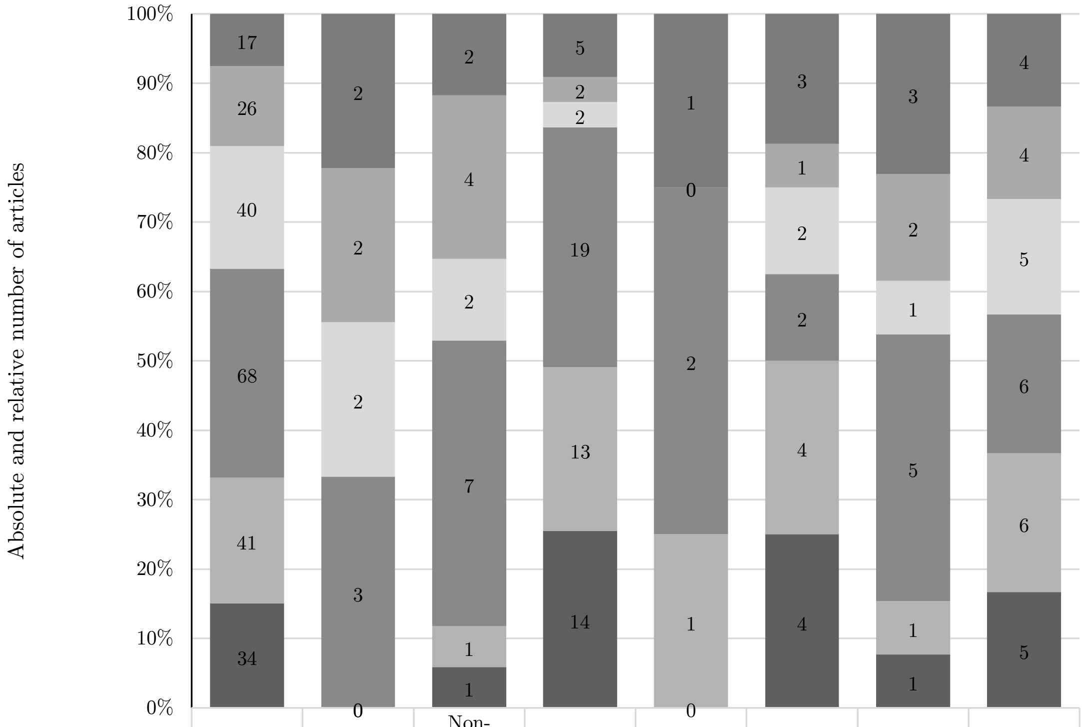
The described classification scheme has been applied to all relevant articles found by our literature research. The detailed classification of all these articles is provided in Tables 2.5–2.10 in Appendix A.

2.3 A brief quantitative evaluation of all papers

Having developed the literature classification scheme, we perform a brief quantitative evaluation with respect to the different dimensions, categories, and attributes to analyse the results and, in particular, to identify common combinations of attributes.

Almost all papers involve a feature of 'energy supply' (dimension A). Especially the combination of attributes from the category 'energy generation' (i.e., energy from the grid/off-site or from an adjustable or non-adjustable on-site facility) with the different 'manufacturing models' (dimension F) provides a good overview of the research in the field of energy-oriented production planning and scheduling. On the one hand, Figure 2.5 shows the number of articles for the possible 21 combinations of attributes linked to the category 'energy supply' and the dimension 'manufacturing model'. By means of this evaluation, it can be directly deduced that by far most studies consider an off-site energy feed from the grid, whereas on-site generation is clearly insufficiently researched. On the other hand, Figure 2.5 also shows the combination of attributes associated with both the category 'coordination mechanism' (e.g., time-of-use, critical peak pricing) of dimension A and the different 'manufacturing models' of dimension F. Here, it can be analysed how many authors consider measures to determine the best timing of energy consumption (demand response). In fact, coordination mechanisms are addressed in only about 60 % of the articles. Furthermore, a distinction between time- and event-driven response is not necessary for the papers that were published so far, as event-driven pricing schemes do not occur so far.

Since all of the papers specify an objective function, we study the different objective



	Grid off-site	Adjustable on-site	Non-adjustable on-site	TOU	CPP	RTP	LCP	Fixed price
Lot sizing	17	2	2	5	1	3	3	4
Other	26	2	4	2	0	1	2	4
Job shop	40	2	2	2	0	2	1	5
Flow shop	68	3	7	19	2	2	5	6
Parallel machines	41	0	1	13	1	4	1	6
Single machine	34	0	1	14	0	4	1	5

Energy supply and coordination mechanism

Figure 2.5: Energy supply and coordination mechanism subject to manufacturing model.

criteria (dimension D, cf. Subsection 2.2.2), as it seems interesting to analyse the relative frequency of the individual objectives proposed. Figure 2.6 shows a pie chart with the corresponding information. Here, the monetary objective functions are shown on the right side (chequered) of the chart and the non-monetary objective functions on the left side (vertical line).

As expected, a large share of the articles (approx. 41 %) deals with energy costs and energy consumption in the objective function. A further large part considers time-based objective functions, which comprises various forms like minimisation of the maximum tardiness, minimisation of total earliness and tardiness, or minimisation of the completion time. Peak power and environmental objectives are integrated into the models less than

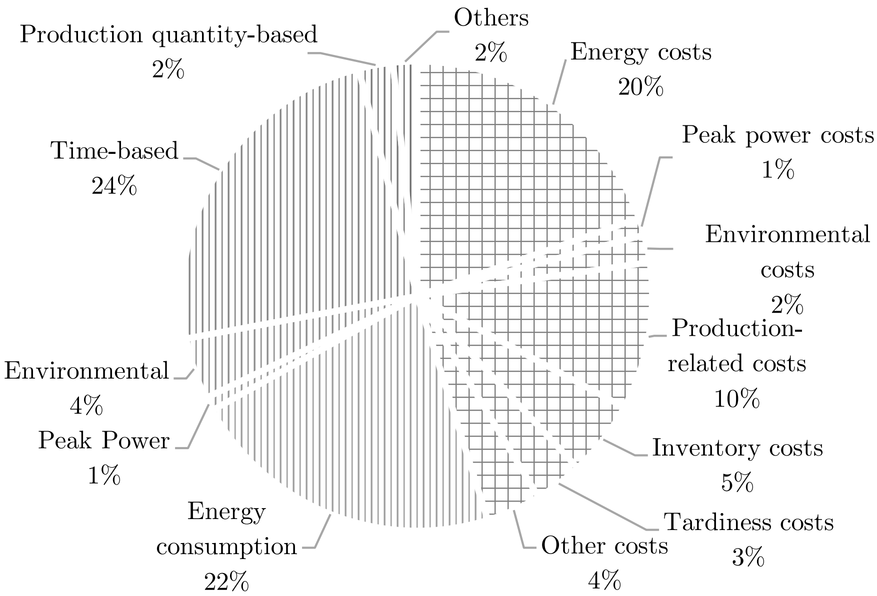


Figure 2.6: Relative usage of objective criteria.

assumed, no matter whether treated by a cost or by a non-monetary objective.

In this survey, energy storage as well as possible energy conversion and reconversion are explicitly taken into account. Therefore, the attributes P2P, P2X, and P2X2P of dimension C in the field of the energy storage types have to be evaluated in combination with the categories 'energy generation' and 'coordination mechanism' of dimension A. Analysis shows that storage types play a subordinate role in the published articles. Merely the simple P2P-storage received some significant attention so far. Thus, a clear gap opens up here for future research.

2.4 Energy-oriented research in machine environments

In Figure 2.1, we have already illustrated that the present literature survey deals with energy-oriented research in the field of production planning and scheduling with a focus on manufacturing environments. However, not only machines should be considered, but also supporting, energy-intensive processes (e.g., transportation), which require electricity to perform or support production. Since conventional machine environments or manufacturing models (dimension F) are chosen as a basis in almost all articles, we will first take a closer look at papers that are positioned in this field; see Subsections 2.4.1–2.4.4. The task of machine scheduling is to schedule jobs on a given set of machines, taking into account any possible dependencies so that the resulting schedule is as good as possible with regard to a defined objective criterion. The result is then a schedule that contains the assignment of individual jobs to the machines as well as information about the order and the timing in which the jobs are processed on the machines (Pinedo 2016). Finally, Subsection 2.4.5 reflects lot sizing problems. This stream of research accounts for determining the number of product units to be processed together on one machine. The different problems can be clearly divided into problems with a single-objective and a multi-objective. In the following, we use this substructure to increase the clarity of the descriptions.

2.4.1 Single machine scheduling

With regard to possible machine environments, the fundamental case is to consider only a single machine. The resulting single machine scheduling problem is practically relevant in various applications that feature a dominant energy-intensive process step (e.g., heating, cooling, coating). Moreover, the problem often appears as a subproblem in environments with multiple machines.

Single-objective

In the context of single machine scheduling, a total of 13 papers with a single-objective criterion can be identified. The most studied setting is a general manufacturing environment of a production company that faces an energy-aware single machine scheduling problem (Zhang et al. 2018a, Módos et al. 2017, Gong et al. 2016, Che et al. 2016, Aghelinejad et al. 2018). Moreover, some articles deal with problems for particular industries like the steel industry (Sinha and Chaturvedi (2018), Puttkammer et al. (2016)) or the production of flake ice units (Ramos and Leal 2017). The paper of Wang et al. (2019a) considers both a single- as well as a multi-objective model that further integrates production scheduling and distribution scheduling. While Wang et al. (2019a) combine single machine scheduling with a multi-vehicle routing problem in an integrated model formulation, Gong et al. (2017) extend energy-efficient production scheduling with labour-scheduling, aiming at investigating the emerging trade-off between low energy and low labour costs, respectively. In general, prevalent problem modifications observe idle machine switch-off strategies and consequently account for non-processing energy demand as well as energy-conscious speed variation due to multi-mode machine characteristics (Lee et al. 2017, Fang et al. 2016). Chen et al. (2019a) consider machine conditions during optimisation in order to evaluate machine reliability in a dynamic, uncertain planning environment. All articles are based exclusively on grid energy supply. The work of Ramos and Leal (2017) also incorporates a P2X storage in the form of ice production. With regard to monetary objectives, roughly 78 % of the articles address goals, where cost are related to energy consumption and production schedules are carried out under a TOU pricing scheme (6 articles) or an RTP scheme (3). Only Módos et al. (2017) include energy consumption limits. Most articles take into account a planning horizon of at most 24 hours (7 articles). Four articles show a mid-term planning horizon (> 24 hours). Merely Che et al. (2016) and Ramos and Leal (2017) address a longer time horizon of up to one month. Three articles do not specify the planning horizon, which places the problem within a generic time frame. Seven out of the 13 papers exhibit MIP formulations, three articles present non-linear model formulations, and another three publications do not explicitly present a model at all. Just Gong et al. (2016) examine stochasticity in terms of machine failures, starvation, blockage of a production unit, and customer order cancellation or changes. In general, except for one paper, the considered articles propose heuristic algorithmic solution methods to produce solutions within reasonable time. Genetic algorithms (Aghelinejad et al. 2018, Gong et al. 2016; 2017), greedy insertion heuristics (Zhang et al. 2018a, Che et al. 2016), a GRASP heuristic (Puttkammer et al. 2016), tabu search (Wang et al. 2019a, Módos et al. 2017), an ant colony algorithm (Chen et al. 2019a), a graphical solution method based on the concepts of pinch analysis (Sinha and Chaturvedi 2018), an approximation algorithm (Fang et al. 2016), and a dynamic idle time and arrival time control algorithm (Lee et al. 2017) can be found in the literature. Furthermore, Che et al. (2016), Chen et al. (2019a) additionally propose an exact solver solution.

Multi-objective

A total of 22 articles deal with multi-objective formulations, which is about 63 % of all articles on single machine scheduling. Considering the trade-off between energy costs and time-based objectives (10 articles) and the combination of energy consumption and time-based objectives (5) is most prominent. 12 models explicitly take energy costs into account, with the majority of them incorporating TOU tariffs as a price coordination mechanism. The production setting investigated in these multi-objective studies is primarily a manufacturing environment similar to the one in the single-objective problems of this field. Only one article deals with a different setting and focuses on energy-aware scheduling of computing device jobs in data centres (Carrasco et al. 2018). Regarding research on manufacturing environment extensions, Liu et al. (2019b) investigate deterioration effects of machines and Cui et al. (2019b) as well as Sin and Chung (2020) consider machine unavailability due to failures, which necessitates to incorporate (preventive) maintenance planning. Li et al. (2017c) and Zhang et al. (2017b) include machine cutting parameter optimisation into process planning and job scheduling. All articles exhibit settings in which the energy is supplied by the power grid. Merely Liu (2016) extends this by an on-site energy generation that also includes a rechargeable battery storage system. It may be stated that nearly 60 % (13 articles) additionally account for non-processing energy demand besides processing energy demand consideration. While ten articles optimise operations for a single day of production (short-term), two articles concentrate on several days (mid-term), and the remaining ten articles do not explicitly specify a planning horizon. With the exception of Zhang et al. (2017b), all articles with a short-term planning horizon comprise time-based components in their objective functions. Apart from various heuristic solution approaches like, e.g., particle swarm optimisation (Li et al. 2017a, Liu et al. 2019b), articles predominantly apply metaheuristics based on ε-constraint methods for the generation of pareto fronts to solve the multi-objective problems (Cheng et al. 2017, Liu et al. 2019a, Wang et al. 2016, Wu et al. 2019a, Che et al. 2017a). Moreover, the non-dominated sorting genetic algorithm (NSGA-II) is often used as a benchmark in order to compare the introduced solution approaches (Liu et al. 2019a;b, Lu et al. 2016).

2.4.2 Parallel machine scheduling

In machine environments with several parallel machines, it has to be decided which machine processes which jobs. Thereby, machines are not necessarily identical, i.e., they may differ in terms of speed, energy consumption, or other characteristics.

Single-objective

In the field of parallel machine scheduling, there are 18 articles dealing with a single-objective function. Only one of them (Zhang et al. 2018c) considers on-site adjustable energy generation and optimises the sizing of the generation unit under critical peak pricing (CPP). All other papers examine production settings in which the underlying factory is connected to the grid, with a multitude of authors assuming a variable pricing structure like TOU tariffs (7 articles) or RTP (3). Nine articles include non-processing energy demands within the machine characteristics. It is rather surprising that no publication takes energy storage into account. As one could already assume from the wide consideration of variable pricing patterns, most objective functions have a monetary focus, with 13 papers putting emphasis on minimising energy costs. Additional cost factors are related to production (6 articles), inventory (5), tardiness (2), peak power (1), and environmental concerns (1). There is only one article aiming at minimising the production system's energy consumption; see Meng et al. (2019b). Regarding the investigated time frame, six papers contain a short-term planning horizon, one paper focuses on a mid-term horizon, and two articles consider a long-term planning horizon. Most authors formulate the parallel machine scheduling problem as a mixed-integer linear model (14 articles), while the use of heuristics is the typical solution approach (17). Modelling approaches such as LP, MINLP, or stochastic modelling are hardly observed (Zhang et al. 2018c, Hajej and Rezg 2019, Yang et al. 2018), while QT and simulation are not present at all. Twelve articles use exact solver solutions. Five of the papers combine lot sizing and machine scheduling, with two of them (Rapine et al. 2018a, Wu et al. 2018a) including decisions of additional machine capacity purchase. Kong et al. (2020b) solve an integrated order acceptance and scheduling model. Yang et al. (2018) investigate a scrap steel production, additionally taking into account the uncertainty of raw material quality.

Multi-objective

Considering multi-objective optimisation for parallel machine environments, 21 papers can be identified. They exclusively deal with settings, where energy is supplied by the grid connection. Energy storage is not considered in any of the papers. The TOU scheme is examined four times and the RTP scheme once, which means that the share of authors investigating variable pricing is significantly lower than in single-objective studies. Consequently, most of the papers make use of non-monetary objective functions being comprised of time-based (18 articles), energy consumption (13), environmental (2), and peak power (1) performance measures. Just seven of the papers minimise energy costs. Merely Kong et al. (2020a) take production-related costs into account, where they use an aggregated cost term that includes cost of machines, labour, material, depreciation, and other variable factors. In nine articles, the parallel machine setting is integrated with a flow shop. (Rocholl et al. 2020) deal with a lot sizing problem in a parallel machine setting and point out that the pure parallel machine problem is rarely considered appropriate for today's complex production environments. Similarly to single-objective optimisation, most of the articles solve short-term problems (7 articles in total). Only two papers deal with a mid-term planning horizon (Zhu and Tianyu 2019, Zheng and Wang 2018). A long-term horizon is studied in two publications (Plitsos et al. 2017, Zeng et al. 2018b). The majority of problems is modelled as a MIP, whereas the two papers of Faccio et al. (2019) as well as Zhu and Tianyu (2019) model a MINLP. A simulation approach including a comprehensive data model for energy-aware manufacturing is presented by Plitsos et al. (2017). All articles use heuristic approaches to find a solution, while two authors also present exact solver solutions for small problem instances.

2.4.3 Flow shop scheduling

In flow shop environments, different production stages exist in series and each job passes the stages one after the other and in the same order.

Single-objective

Roughly a third of the investigated flow shop problems (26 articles in total) can be associated with single-objective optimisation. All these articles assume that energy is supplied by the external grid. Interestingly, two papers put emphasis on adjustable on-site generation systems. While Islam et al. (2018) do not explicitly describe the underlying system, the core element in Biel and Glock (2016a) relies on the transformation of waste heat into electricity. The waste heat is generated during machine operations of other production systems and then converted into electricity that is used to operate the machines in the flow shop (P2X, but no storage system). The integration of non-adjustable on-site generation systems is considered by five articles, while predominantly the feed-in of solar as well as wind power systems is of particular interest. Among all energy cost-related objective functions, which make up about 65 % of the considered articles, the most often studied coordination mechanism are TOU tariffs. Fazli Khalaf and Wang (2018) is the only work which incorporates an RTP scheme that is adapted to a short-term scheduling problem. Moreover, the impact of on-site renewables such as solar and wind power as well as battery storage systems are taken into account here, allowing to investigate related make-or-buy decisions of energy supply. Next to a specific production process, the work of Dababneh et al. (2016) also takes up a heating ventilation and air conditioning system, being referred to as other energy-intensive processes (cf. Subsection 2.2.2. The basic idea is to optimise the heat transfers such that peak power demands can be flattened significantly. Among all papers that explicitly state a planning horizon, short-term scheduling is most popular (10 articles). In contrast, Zhang et al. (2018c) study the sizing and planning of an on-site generation system on a yearly basis, while a CPP tariff is considered. This approach stands out, since it is the only article that covers both a long-term planning horizon as well as the CPP tariff. Generally, different heuristic solution strategies are used in 19 articles. Genetic algorithms are presented, e.g., in Liu et al. (2017b), Meng et al. (2019b), Zhang et al. (2018c), and Masmoudi et al. (2017b). Moreover, a fix-and-optimise (Liang et al. 2019) as well as a fix-and-relax (Rodoplu et al. 2019) approach can be named further on, while exact approaches are applied less often (9 articles).

Multi-objective

Looking at multi-objective optimisation in the context of flow shop scheduling, a total of 42 papers can be found here. Similar to the single-objective flow shop papers, also all of the multi-objective articles assume a grid feed-in. The works of Biel et al. (2018), Wu et al. (2018b), and Weitzel and Glock (2019) additionally study the impact of on-site generation, where the latter also incorporates a battery storage system. Solar and wind generation, respectively, are treated as a non-adjustable source of electricity in these modelling approaches. A clear majority of studies (26 articles) analyses the trade-off between energy consumption and time-based objective criteria (i.e., makespan), see, e.g., Fu et al. (2019), Jiang and Wang (2019), and Öztop et al. (2020). Considering monetary objectives, roughly a quarter of the articles combines energy cost-related goals with the aforementioned time-based objective criteria, mostly carrying out short-term production scheduling under a TOU pricing scheme. In this line of thought, Masmoudi et al. (2017a) is worth mentioning, as this study combines a multi-objective flow shop environment with a single-item capacitated lot sizing problem in order to minimise setup and inventory costs. Regarding the planning horizon, 23 articles consider a horizon of at most 24 hours and 14 articles do not specify the horizon. While four papers focus on a planning horizon slightly longer than 24 hours, only Zeng et al. (2018b) address a longer time horizon of up to one month by interpreting the computed energy-saving ratios also on a monthly basis. The most widely used solution strategy relies on determining pareto-optimal solutions by means of heuristic approaches such as the hybrid NSGA and its variants (e.g., Schulz et al. (2019), Wang et al. (2019b), and Zheng et al. (2019)). Ten articles (additionally) make use of exact solution approaches for verification purposes, see, e.g., Weitzel and Glock (2019) and Schulz et al. (2020).

2.4.4 Job shop scheduling

A job shop environment is characterised by several production stages (machines), where each job must pass through the stages, but following its own predefined route (machine sequence).

Single-objective

Within the field of job shop scheduling problems, 12 articles present single-objective models. Six papers study energy costs and five energy consumption. Three papers deal with tardiness penalties and two with non-monetary time-based objectives. Moreover, two articles also consider production-related costs and one article includes inventory costs. The authors either optimise operations for a planning horizon of a single day (5 articles) or they do not specify the time frame for the optimisation (7 articles). Only three articles present exact solutions, the rest uses heuristics.

Among the papers in this area, only Golpîra et al. (2018) consider an industrial setting with on-site energy generation (adjustable and non-adjustable), P2P, and P2X2P energy storage. The authors introduce an integrated, robust mixed-integer problem for lot sizing and scheduling decisions under uncertain energy supply and demand, minimising energy as well as various production-related costs. Two other articles also present integrated models. Ebrahimi et al. (2020) combine machine scheduling and layout optimisation, where distances between machines influence transportation times that may contribute to tardiness penalties. Zhang et al. (2016b) integrate scheduling and process planning for environments, where different product types have a number of possible machine sequences (processes). The traditional time-based objectives are considered in Meng et al. (2019c) and Meng et al. (2019a). Here, the authors reduce energy consumption in production by minimising the idle times of machines in which they still consume energy. In Masmoudi et al. (2019), the authors compare two different problem formulations of energy-aware job shop scheduling: a time-indexed versus a disjunctive graph-based formulation. The results show that the time-indexed formulation takes longer to find feasible solutions, but, eventually, reaches the optimal solutions faster than the disjunctive formulation. Some articles propose rather unusual nature-inspired metaheuristics, namely cat swarm and water wave algorithms (Jiang and Deng 2018), a discrete whale algorithm (Jiang et al. 2019), and a bat algorithm (Lu and Jiang 2019).

Multi-objective

In total, 22 articles focus on multi-objective optimisation problems in a job shop environment. All of them study settings in which the production site receives its energy from the power grid; on-site energy generation or storage is not regarded. Mainly, a one-day planning horizon is taken into account, only two articles schedule several days and one includes a long-term perspective. In the area of multi-objective optimisation, most of the papers examine trade-offs between classical time-related objectives (i.e., makespan, tardiness, or waiting time) and energy consumption or environmental objectives such as emissions reduction (17 articles). Only a minority (6 articles) use monetary objectives, with four models taking energy costs into account and only one of them including TOU and RTP tariffs as coordination mechanisms. The predominant solution approach to get to an efficient frontier is a variation of the genetic algorithm, mainly the NSGA-II.

One of the most studied settings in multi-objective job shop problems is an industrial environment in which machines can operate at variable processing speeds under corresponding energy consumption rates (Wu et al. 2019b, Abedi et al. 2020, Zhang et al. 2017b, Mokhtari and Hasani 2017, Wu and Sun 2018, Salido et al. 2016, Luo et al. 2019). Frequently, the consideration of deterioration effects is included and, thus, maintenance activities on machines are scheduled together with production jobs (Wu et al. 2019b, Abedi et al. 2020, Zhang et al. 2017b, Mokhtari and Hasani 2017). Since these models focus on processing speeds, time-related objectives are associated with a minimisation of energy consumption or CO_2 emissions. As jobs move individually between stages in this production environment, a natural modification of the basic setting is to incorporate (energy-intense) transportation activities into the model. Depending on the environment, either cranes (Liu et al. 2019c) or automatic guided vehicles (Dai et al. 2019, Zhang et al. 2019e) are included. To account for both, service objectives and environmental objectives, minimisation of transportation times, and makespan is combined with a minimisation of energy consumption. Furthermore, Gong et al. (2019) take workforce-related aspects into account by using wages as cost-factors. In a related stream, Coca et al. (2019) and Gong et al. (2018) add non-monetary social objectives, e.g., noise or material handling, to bring a sustainability perspective into the job shop scheduling problem. Perković et al. (2017) only optimise monetary objective values (tardiness and energy cost), but use a weighted sum approach to generate Pareto fronts, which is why the article may be classified as a multi-objective approach. Especially in more dynamic environments, optimisation needs to account for possible machine breakdowns or random job arrivals (Li et al. 2020, Zhang et al. 2016a). Solution approaches then take a pre-generated production schedule that is modified when dynamic events occur through introducing new genes into the used genetic algorithm. Wang et al. (2018b) consider applications that involve consecutive steps in the production processes (e.g., tool selection and machine allocation). They divide the problem into subproblems which are solved within an iterative two-stage approach. Finally, game theoretical approaches are also applied to reach an equilibrium of conflicting objectives within job shop production environments (Zhang et al. 2017c, Wang et al. 2020a).

2.4.5 Lot sizing

Lot sizing decisions are about the aggregation of different production orders into production lots whose production is preceded by a setup process.

Single-objective

We identified a total of 16 papers on energy-oriented lot sizing that follow a single-objective optimisation. Fourteen of these papers address period-discrete lot sizing decisions to fulfil given demands and two of them deal with time-continuous lot sizing decisions (Asghar et al. 2019, Biel and Glock 2016a). Regarding the energy supply, all papers consider using energy from the grid. On-site energy is additionally treated in one paper as adjustable (Biel and Glock 2016a), in one paper as non-adjustable (Wichmann et al. 2019b), and one paper includes both options (Golpîra et al. 2018). Eight papers include time-varying energy prices, mostly as TOU tariffs (Masmoudi et al. 2017a;b, Rocholl et al. 2020, Rodoplu et al. 2019, Tan et al. 2018) or real-time prices (Golpîra et al. 2018, Wichmann et al. 2019a;b), while one paper also addresses critical peak pricing (Masmoudi et al. 2017a). When looking at infrastructure, it is noticeable that energy storage is only covered by two papers, once as P2P (Wichmann et al. 2019b) and once as P2P and P2X2P (Golpîra et al. 2018). Optimisation decisions always refer to monetary objectives. Energy costs (11 articles), production-related costs (15 articles) as well as inventory costs (15 articles) are the most important cost types in lot sizing. It is remarkable that in eight articles, energy costs are directly derived from the amount of energy used, while in three articles energy cost are derived from emission certificates. The major cost types are accompanied by peak power costs (Hajej and Rezg 2019, Masmoudi et al. 2017a;b, Rodoplu et al. 2019), environmental costs (Absi et al. 2016, Biel and Glock 2016a, Hong et al. 2016), and tardiness costs (Giglio et al. 2017). Further eight papers deal with other costs like, e.g., penalties for violating of contract bounds or delayed demand fulfilment. Regarding the machine characteristics, 12 papers address a single mode of machines, while five papers consider multiple operation modes. The models are typically based on MIP formulations (15 articles), one paper formulates a MINLP (Hajej and Rezg 2019), and two papers focus on stochastic models (Asghar et al. 2019, Golpîra et al. 2018). To solve the proposed models, heuristics solution procedures (9 articles) as well as exact algorithms (5) and exact solvers (9) are presented.

Considering the modelling of time in the decision making, two different approaches can be distinguished. Some papers use a continuous time, while most papers use discrete time periods. In the field of time-continuous lot sizing, Asghar et al. (2019) examine the determination of recurring production lots with respect to their related production speed. The speed influences energy consumption as well as emissions. The lots are determined using partial differential equations. Furthermore, Biel and Glock (2016a) consider a complex two-stage production and energy system. Here, a waste heat recovery uses energy obtained from prior periods to fulfil energy demands of current periods. To do so, complex engineering knowledge is applied to determine and formalise energy-related non-linear interdependencies and to evaluate saved amounts of primary energy. The economic aim is the decision on production lots according to interrupting and non-interrupting production policies. Optimal decisions are obtained by solving differential equations. In the field of time-discrete lot sizing, decisions on the setup state of machines as well as production quantities of products are derived for multiple discrete periods in a row. In all approaches, inventory costs as well as period-based capacities prevent a one-time setup process for the overall planning period. These classic approaches are extended by the consideration of energy-prices by Giglio et al. (2017). One interesting aspect of energy-related constraints are emission quantities and allowances as well as energy availability. Absi et al. (2016) include emission allowances and set up a model to decide whether to use emission-friendly yet slow or energy-intensive yet fast production modes to fulfil a given demand. Rapine et al. (2018a) and Rapine et al. (2018b) study limited availability of energy in lot sizing and develop several exact solution methods for the determination of lots of individual products to be produced in multiple stages. Hong et al. (2016) consider emission allowances in the selection of machines to be set up and used for production. Tan et al. (2018) take into account minimum and maximum load restrictions on the energy consumption per period.

If energy can be bought at an arbitrary amount, its consumption is evaluated with energy costs. Here, Giglio et al. (2017), Masmoudi et al. (2017b), and Wichmann et al. (2019a) enhance classical lot sizing approaches for different machine environments by the consideration of energy costs for production as well as setup and idle processes. Rodoplu et al. (2019) extend the decision space even to the selection of energy supply contracts and provide a fix-and-relax heuristic to solve the problem. Studies that go beyond the consideration of a production are Wichmann et al. (2019b) and Golpîra et al. (2018). Wichmann et al. (2019b) introduce an on-site energy generation as well as an electrical energy storage to determine interactions between production decisions and the energy market as well as the economic benefit of including energy storage within production systems. Golpîra et al. (2018) develop a robust method for the integration of a wind turbine and a combined heat and power plant into the energy supply of a multi-stage production system. In both approaches, problems are solved using standard solvers.

Furthermore, both approaches show that incorporating decisions for energy supply leads to different schedules than just production-related ones.

Multi-objective

Merely the paper of Rocholl et al. (2020) investigates multi-objective lot sizing. It focuses on a bi-objective planning approach for the batching of jobs to lots on parallel identical machines. The two objectives consider energy costs as well as weighted tardiness of jobs. Energy costs refer to TOU tariffs of the energy that is demanded by jobs in their processing periods. Energy is provided by the grid. The proposed bi-objective problem is solved by an NSGA-II heuristic that uses various encoding and local search schemes. The procedure is applied in a case study to derive a pareto-optimal frontier of the competing objectives, showing the possible spread and trade-off between them.

2.5 Streams of recent developments and future research potentials

The analysis shows that the body of literature has been growing significantly since the first review papers have been published. In what follows, we complement the quantitative perspective taken so far by a content analysis. As a starting point, we use the open research areas that have been identified by Gahm et al. (2016) as well as Biel and Glock (2016b) and enrich them through a discussion of recent, innovative research streams found in the contemporary literature. The goal is to provide an updated research agenda for energy-aware production planning and scheduling.

Likewise, a presentation of real-life case studies allows to identify specific industries, where energy-aware scheduling is mostly carried out. Table 2.3 provides an overview of the studied articles that specifically look into practical manufacturing processes. In the listed references, each of the individually developed model formulation is directly applied to a specific use case in industry. As expected from Section 2.1, several practical applications can be found in the energy-intensive steel and paper industry, see, e.g., Lu et al. (2016), Sinha and Chaturvedi (2018), Zeng et al. (2018b;c). Interestingly, also CNC machine tool processes are widely studied. In these cases, the energy consumption is typically affected by different processing speed levels (e.g., Zeng et al. (2018a), Wang et al. (2020c)). Looking at the evaluation by country, roughly 45 % of real-life case studies are located in China, not the least because of governmental efforts of fostering energy-conscious transformation in the industry sector (Li and Lin 2017, Ghisellini et al.

Table 2.3: Overview of articles dealing with real-life case studies.

Study	Industry	Country	Manufacturing Model
Biel and Glock (2016a)	Cutting process	unknown	Flow shop, Lot sizing
Che et al. (2016)	Milling/boring of metal parts	China	Single machine
Che et al. (2017b)	Turning machines	unknown	Parallel machine
Chen et al. (2019a)	Rotor production	China	Single machine
Chen et al. (2019b)	Milling/machining	unknown	Other
Coca et al. (2019)	Metal-mechanic sector	Colombia	Job shop
Feng et al. (2020)	Auto parts (one-line shafts)	China	Other
Gajic et al. (2017)	Steel scrap melt shop	Italy	Flow shop
Iqbal and Al-Ghamdi (2018)	Metal-cutting processes	unknown	Job shop
Li et al. (2017a)	CNC face milling process	unknown	Single machine
Li et al. (2018a)	Bathroom ceramic plant	China	Flow shop
Li et al. (2017b)	Hydraulic press system	unknown	Single machine
Li et al. (2017c)	Manufacturing workshop	unknown	Single machine
Li et al. (2018c)	Welding shop	China	Flow shop
Liang et al. (2019)	Tea drink production line	China	Flow shop
Liu et al. (2017a)	Ceramic tile polishing	unknown	Flow shop
Liu et al. (2019c)	Cement equipment	China	Job shop
Liu et al. (2019d)	Cement equipment	China	Other
Liu et al. (2020b)	Ring forging	China	Flow shop
Lu et al. (2016)	Steel forming	unknown	Single machine
Lu et al. (2017)	Connecting rods of motors	China	Flow shop
Modarres and Izadpanahi (2016)	Smelting manufacturer	Iran	Other
Nujoom et al. (2019)	Plastic and woven sacks	unknown	Other
Plitsos et al. (2017)	Textile manufacturing	unknown	Parallel machine, Job shop
Puttkammer et al. (2016)	Hot strip mill rolling	unkown	Single machine
Ramezanian et al. (2019)	Extractor hood production	Iran	Flow shop
Ruiz Duarte et al. (2020)	Metal structures	Mexico	Flow shop
Shi et al. (2019)	Part machining	China	Flow shop
Sinha and Chaturvedi (2018)	Iron and steel plant	India	Single machine
Su et al. (2017)	Pharmaceutical enterprise	China	Flow shop
Tan et al. (2019)	Iron and steel plant	China	Other
Wang et al. (2018b)	CNC machining	unknown	Job shop
Wang et al. (2020b)	Television disassembly	China	Other
Wang et al. (2016)	Glass manufacturing	China	Single machine
Wang et al. (2019b)	Glass ceramic production	China	Parallel machine, Flow shop
Wang et al. (2018c)	Automobile stamping die	China	Parallel machine, Flow shop
Wang et al. (2020c)	CNC machine tool	unknown	Other
Wu et al. (2018b)	Wind turbine/tire production	China	Flow shop
Yang et al. (2018)	Steel scrap melt shop	unknown	Parallel machine, Flow shop
Zeng et al. (2018a)	CNC machine tool	China	Parallel machine
Zeng et al. (2018b)	Tissue paper mill	China	Flow shop
Zeng et al. (2018c)	Paper mill	China	Parallel machine, Flow shop
Zhang and Jiang (2019)	CNC machine tool	unknown	Single machine
Zhang et al. (2018a)	Vertical machining centre	China	Single machine
Zhang et al. (2018c)	Auto components	USA	Parallel machine, Flow shop
Zhang et al. (2016b)	CNC machine tool	unknown	Other
Zhang et al. (2019e)	CNC machine tool	unknown	Job shop
Zhao et al. (2018)	Steel production	unknown	Flow shop

2016).

From the future research needs, identified in the mentioned reviews of Gahm et al. (2016) and Biel and Glock (2016b), three main categories of future development of energy-aware production planning approaches can be derived. As outlined in Section 2.1, these categories are *system boundary*, *conceptualisation*, and *practical relevance*. Table 2.4 now shows the three categories with the individual areas in more detail. Please note that the areas are marked with abbreviations to refer to them later in Figure 2.7. In the category 'system boundary', it is interesting to identify contributions that deal with efficiency increases of the upstream processes of energy supply. Pricing perspectives of the utilities are rarely considered and are therefore an area of future research. Systems differ, especially, if an internal conversion system is available or if on-site generation and storage is installed. It is also of interest to find out whether load management is implemented, where, e.g., power demand charges are included. Other fields incorporate multiple-site concepts with energy hubs and smart grids in an industrial symbiosis. The category 'conceptualisation' emphasises that a better understanding of the energy characteristics is to be advocated. Since all systems under consideration are highly technical, the consideration of interacting technologies is an important issue. Usually, a stochastic dynamic environment is given and authors should be aware of it. Few papers explicitly model other output-related criteria like the carbon footprint. In addition, few approaches are presented that deal with big data and use methods of machine learning. A linkage between short-term scheduling and mid-term planning in a common approach can help to consider long-term effects in short-term decisions. The 'practical relevance' category addresses whether an approach or a case study offers added value for the industry. In particular, realistic model formulations or suitably specialised and useful solution methods should be identified. It is valuable if authors provide synthetic benchmarks that can be used to validate methods in the future. Furthermore, real-life case studies show that consulting activities in practice form the basis of the contribution.

Generally, we observe that substantial progress has been made along all the identified areas of future developments. A number of works stand out as they address multiple aspects at once. Such papers that contribute to several categories and their involved subareas have been taken up in Table 2.4. Figure 2.7 further visualises to what extend the categories are addressed in the literature. In this figure, we have also taken up papers that contribute to just one of the three categories, but then have a lighthouse character in doing so. From Table 2.4 and Figure 2.7, it can be seen that substantial progress has been achieved in the recent literature, which is a promising finding regarding the development of the research field.

In order to further advance research in the field of energy-aware production management, we abstain here from discussing the aforementioned categories and subareas in detail and refer to the descriptions in the earlier survey papers. Instead, we suggest to change the perspective on recent developments by discussing in the following subsections,

Table 2.4: Recent contributions to open research areas mentioned in earlier literature reviews.

	Biel et al. (2018)	Biel and Glock (2016a)	Cui et al. (2019a)	Fazli Khalaf and Wang (2018)	Golpîra et al. (2018)	Perković et al. (2017)	Pham et al. (2019)	Ruiz Duarte et al. (2020)	Weitzel and Glock (2019)	Wu et al. (2018b)	Zhang et al. (2018c)
Category: System boundary											
Efficiency increase of upstream processes (IUP)	○	○	●	●	●	○	○	●	○	○	○
Price setting perspective of utilities (PPU)	○	○	○	○	○	○	○	○	●	○	○
Internal conversion system (ICS)	○	●	○	○	●	○	○	○	◑	○	○
On-site generation and storage (OGS)	◑	◑	●	●	●	●	●	●	●	●	◑
Load management; including power demand charges (LM)	●	○	●	○	●	○	○	●	●	○	●
Multi-site concepts (MSC)	○	○	○	○	○	○	●	○	○	○	○
Category: Conceptualisation											
Better understanding of energy characteristics (EC)	○	●	○	○	○	○	○	○	○	○	○
Stochastic dynamic environment approaches (SDA)	●	○	◑	●	●	○	●	●	○	○	○
Modeling of output-related criteria (ORC)	○	○	○	○	○	○	◑	○	○	●	○
Big data and machine learning approaches (BDML)	○	○	◑	●	◑	○	●	○	○	○	○
Linkage between scheduling and mid-term planning (SMP)	○	○	○	○	○	●	●	○	○	○	○
Category: Practical relevance											
Realistic model formulations (RMF)	●	●	●	●	●	●	○	●	●	●	●
More specialised and useful solution methods (SUM)	●	●	●	○	○	○	○	○	○	●	●
Synthetic benchmarks for validation (SBV)	○	○	○	○	○	○	●	○	○	○	○
Real-life case studies (RCS)	◑	●	○	◑	○	○	○	●	○	◑	●

● fully covered, ◑ partially covered, ○ not covered

what main thematic *research streams* we identified from analysing these innovative studies. Within Subsections 2.5.1–2.5.6, we take up the articles from Table 2.4 and Figure 2.7 and show how they form streams of recent development with respect to (novel) problem features such as on-site electricity generation, layout and process planning, integration of assembly line balancing, and others. Some of these steams are already addressed through a substantial number of papers, whereas others are more in their beginning. Through the identification of these streams and the discussion of corresponding papers, we identify promising gaps for future research.

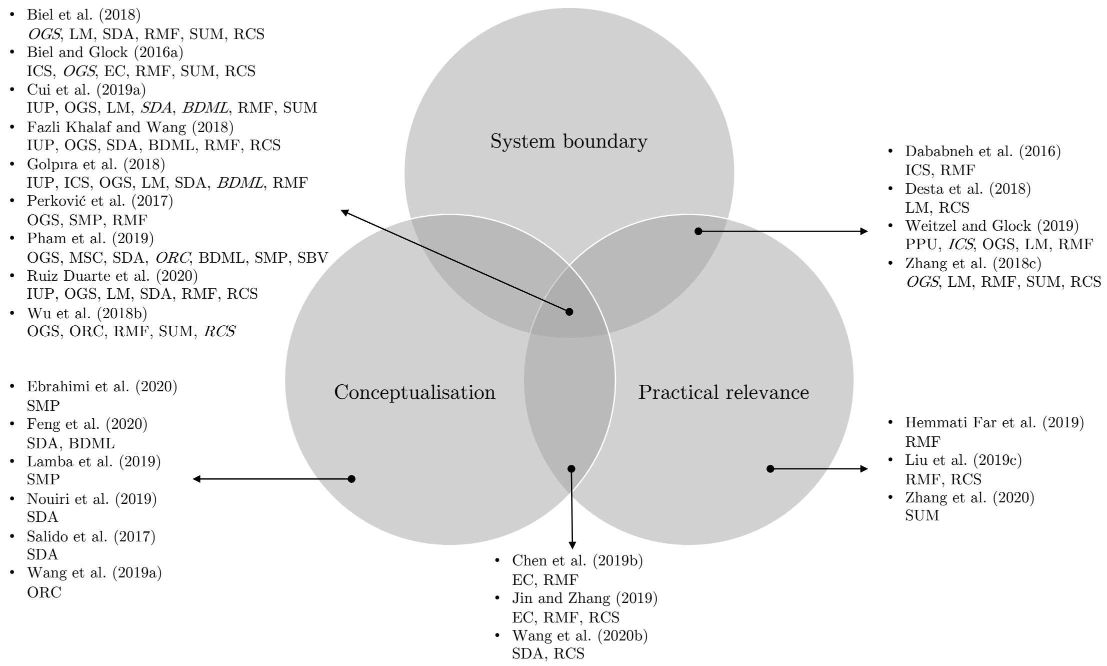


Figure 2.7: Contribution of innovative research articles to three categories of research gaps.

2.5.1 On-site generation environments

With an increasing awareness for the possibilities and potentials of on-site generation of energy from distributed (renewable) energy resources to achieve efficient and possibly carbon neutral operations, recently a number of works has been proposed to tackle the challenges of the design and operation of such systems in different manufacturing environments.

Works on *design* intend to support and coordinate decisions on the sizing of on-site energy resources, storage, and energy conversion systems with those of production planning. Mostly, complex energy management scenarios are considered, which comprise realistic load management and demand response mechanisms. Within this stream Zhang et al. (2018c) consider the setting of a manufacturing company participating in a CPP demand response program. Assuming deterministic framework conditions and a non-renewable adjustable energy resource, a MINLP model is proposed to determine the on-site system size and the corresponding production and inventory decisions that minimise the yearly energy costs in the face of variable energy and demand charges. The authors develop and analyse a case study based on an automotive component manufacturer in combination with real CPP data. In order to find solutions, linearisation techniques for the MINLP are presented and complemented by a genetic algorithm. Results show that an optimal design of the system in combination with CPP can lead to cost reductions of approximately 40 %.

The integrated energy system design and warehouse sizing problem is discussed in Perković et al. (2017). The authors consider a stylised factory with a single-stage production process that requires heat and electricity. The intensity of the production process can be varied along with energy requirements. A warehouse (1) provides additional flexibility to serve demand. Heat and electricity are supplied by an on-site fuel-driven combined heat and power plant (2), a power-to-heat unit (3), and a solar power unit (4). Energy can be stored by means of a thermal buffer (5) and traded with the grid via a power exchange unit (6). Assuming deterministic data, a MIP is formulated to simultaneously optimise the sizing of (1) to (6) along with energy trading, fuel purchasing, and adjustments of the production intensity with respect to investment and energy costs. A detailed scenario analysis shows that operating costs have a higher significance than investment costs and when relying on renewable energy generation, bigger energy storage and warehouses are needed.

Pham et al. (2019) study the coordination of decisions on the sizing and locating of on-site non-adjustable energy generation and storage as well as production, inventory, and transports for a multi-item, multi-factory supply chain under an microgrid which is disconnected from the main grid. The objective is to minimise levelised costs assuming stochastic demand and energy supply. To tackle the problem, Pham et al. (2019) use a two-stage approach in which firstly production is scheduled to meet uncertain demands and, afterwards, sizing (i.e., capacity) and positioning (among the set of manufacturing facilities) of solar and wind power units is planned. Based on numerical experiments and detailed 11-year climate data for eight cities around the globe, the authors conclude that net-zero energy operations could be feasible and affordable depending on climate conditions and the ability to exchange energy with the grid. In a sensitivity analysis, the authors also investigate the use of batteries, concluding that they are most valuable in systems that rely on energy from solar power.

From an *operational point* of view, the challenge that comes with on-site generation is to coordinate the diverse set of flexibility instruments in the areas of energy, production, material, and (back)orders in the face of dynamic and/or stochastic energy supply. Deterministic settings are presented in the works of Weitzel and Glock (2019) and Wu et al. (2018b). Weitzel and Glock (2019) consider the energy-aware scheduling of a flexible flow shop with parallel machines and buffers. The system includes on-site solar power generation and a battery storage subject to wear. Additional energy is supplied from the grid.

The main idea is to offer load reduction flexibility to the grid under a demand response regime. Given a baseline schedule and the corresponding load, the authors determine load reduction curves (LRC) that make load reduction potentials and their consequences for the manufacturing firm transparent to the grid operator. This enables the grid operator to select the most efficient load reduction(s), if needed. Within a deterministic model setting, the authors propose an ε-constraint approach to determine LRC for a given set of demand response periods throughout one day. The approach is evaluated based on a numerical study that replicates metal parts manufacturing for an exemplary day. The authors find that the battery contributes to an increased load reduction potential while at the same time reducing the deteriorating effect of demand response interventions on the schedule. The potential, however, comes at the costs of significant wear.

Wu et al. (2018b) investigate possibilities to reduce the carbon footprint of a flexible flow shop using renewable and non-renewable energy sources as well as a battery energy storage system. Based on the assumption that processing and non-processing energy requirements differ based on the energy source, a deterministic multi-objective scheduling problem is formulated to reflect the trade-offs between makespan and the carbon footprint of energy consumption. The latter is derived from a fixed coefficient of CO_2 emissions. A hybrid genetic algorithm with variable local search is proposed to determine non-dominated solutions. Experiments conduced are based on data derived from the production of wind turbine blades and radial tires. Based on the results, the authors conclude that the availability of energy from on-site energy resources allows for a significant reduction of the carbon footprint without jeopardising makespan. Further reductions are possible, however, at the costs of an increased makespan. The proposed solution procedure proved effective in finding non-dominated solutions.

A series of works departs from the assumption of known input data. Golari et al. (2017) present a three-step approach to optimise production and inventory decisions in a multi-site environment with non-adjustable on-site energy supply. The first step of the approach solves a deterministic model for production and inventory planning, assuming renewable energy is always available. In the second step, a multi-stage stochastic optimisation incorporates uncertainties of renewable energy generation. The third step is a Benders decomposition approach to find the optimal production schedule based on scenario trees. The authors determine a pareto front, showing that without high cost increases, a share of approximately 40 % renewable energy consumption can be achieved.

A two-stage bi-criteria stochastic optimisation procedure is contributed by Biel et al. (2018). The authors determine a production schedule as well as energy supply decisions for flow shop systems with grid-integrated on-site wind power to minimise the total weighted flow time and expected energy cost under power and demand charges. A weighted-sum approach is proposed to determine non-dominated solutions. To adequately capture the uncertainty of wind energy supply within the proposed MIP formulation, the authors rely on the physically well-founded wind power scenario generation process of Ma et al. (2013) in combination with a scenario reduction algorithm. At the first stage, the optimisation procedure determines the schedule and establishes an initial plan for the usage of energy generated on-site. The second stage anticipates the flexibility to adjust the energy plan depending on the observed wind power data. A rule-based method is proposed to actually adjust energy supply decisions in real-time as wind power data becomes available. Based on a synthetic case study that replicates real-life data on machine power requirements, a TOU tariff, and wind speed observations, the authors see a strong potential of on-site wind power generation. This potential includes the reduction of energy costs, the mitigation of fluctuating energy prices, and the chance to foster environmental goals in manufacturing. Noteworthy, pronounced reductions in costs can be achieved at a minor increase in total weighted flow time.

A more general system configuration is considered in Cui et al. (2019a). Electricity is fed from the grid and, in addition, energy is generated from a set of non-controllable renewable energy resources and partly stored in an energy storage system. A non-linear model formulation is proposed to minimise electricity costs under demand and power charges for a flow shop system. A general probability distribution function for the shop's energy requirements is derived based on a Markov process that assumes a Bernoulli reliability model. Energy that cannot be used locally will be wasted, as there is no sale to the grid considered. A rolling horizon approach is adopted in order to handle the uncertainty caused by weather changes. To solve the model, the authors present a generalised Benders decomposition method. While referring to a representative production line with six machines and realistic data, the authors demonstrate the suitability of the solution approach. For a static setting, they observe a major potential to reduce energy costs of up to more than 30 %, depending on the size of the on-site energy resources. The rolling horizon scheme shows promising potential to tap the potential in a dynamic setting.

In the same line of thought, Ruiz Duarte et al. (2020) consider a multi-stage production process with on-site renewable energy supply along with energy storage systems and the power grid as backup system. As a special feature, a more realistic energy storage model is used that considers imperfect charging/discharging efficiencies. Production is planned using an aggregate multi-period single-item scheduling model. In order to capture renewable uncertainties, a two-stage robust optimisation model is formulated and a nested column-and-constraint generation algorithm is applied. Similar to the prior works, the authors integrate TOU tariffs combined with LCP, describing an increase in price the more power is consumed in a certain time span. In addition to that, the authors consider energy consumption reduction requests from the utility company. Results based on the case of a metal structures-manufacturing company and a planning horizon of up to seven days demonstrate a cost reduction potential of up to 29 %, where the majority of the cost reductions is only possible with the proposed pricing scheme. Otherwise reductions are limited to only 2 %. Both more incorporation of more detailed data and the consideration of a longer planning horizon help in improving the results.

Finally, Fazli Khalaf and Wang (2018) extend the scope to the consideration of two electricity markets: the day-ahead and the real-time market. The paper refers to a single-item flow shop setting with multiple on-site solar and wind power units as well as a battery-based energy storage system with realistic charging/discharging efficiency. Interaction with the external grid is considered with respect to buying and selling energy. The authors present a two-stage stochastic MIP to minimise electricity costs, given a defined production volume. Based on known day-ahead electricity prices and the forecast of renewable electricity generation, the first stage determines optimal purchase commitments. The second stage anticipates real-time energy procurement by considering scenario-based RTP and the actual generation of the solar and wind power. A synthetic case study is developed based on real data of electricity pricing and renewable generation. In an attempt to make the model more realistic, the authors consider different seasons, distinguish process- and non-process-related energy demand, and include levelised cost of solar and wind generation to incorporate investment-related costs. They observe very substantial cost savings potentials of up to 68 % depending on the number and kind of on-site energy resources. The size of the battery only marginally influences the results. It may be worth noting that the results strongly depend on the data. The charging/discharging efficiency of 90 % in combination with the possibility to sell to the grid at a fixed tariff make the battery an unattractive alternative in many situations. Moreover, the authors assume a strictly positive contribution margin for wind power. As a result, it is easily possible to end up with negative energy costs by adding more and more wind power generation capacity.

To conclude, substantial progress has been made in the conceptualisation, development, and analysis of models to support the design and operations of manufacturing operations with on-site energy generation and storage. The studies consider a wide range of configurations with respect to the energy and manufacturing system and report in unison very significant potentials to reduce costs and to increase the share of renewables. While the potentials obviously depend on the operating conditions (e.g., availability of wind and solar power, operational flexibility, possibility to trade exchange with the grid, dynamic tariffs), there also seems to be a chance to improve the results by relying on more accurate and more holistic models. This can be seen as a strong motivation to engage in the development of extended model formulations as well as the provision of capable solution procedures. When doing so, open topics for future research are the consideration of mid-term energy procurement decisions as well the incorporation of more realistic production costs. With regard to the latter, all model formulations discussed before rely on highly stylised models of production cost. What is missing are model formulations that adequately capture the costs related to the production mode/machine state (e.g., ramp-up costs) as well as those related to the duration and time of the production activities (e.g., labour costs). While data on weather and energy information is widely and publicly available, the same would be highly desirable for open source data sets that reflect the operating conditions of representative manufacturing facilities.

2.5.2 Layout and process planning

A number of authors have identified that planning tasks related to the choice of layout, processes, and tool parameters can have a great effect on schedules as well as their energy profiles.

In most multi-stage production settings, schedules and their energy profiles strongly depend on the allocation of the machines on the shop floor, mainly through the transportation activities between the machines. Not only the production layout has an influence on transportation times, and thereby waiting and idle states of machines, but also the transportation devices themselves. For example, automated guided vehicles (AGVs) or cranes cause the energy consumption to increase. Therefore, another stream of research is devoted to combined production layout planning and scheduling. Ebrahimi et al. (2020) plan the optimal schedule and layout in a single optimisation step. For transportation between machines, electric vehicles are used which also contribute to the energy demand. It is shown that the combined planning (energy and tardiness) results in cost savings of 5 % on average. Lamba et al. (2019) optimise a dynamic cell layout by minimising energy consumption costs incurred by AGV movements as well as material handling and rearrangement costs. The resulting non-linear problem is solved by a simulated annealing-based metaheuristic.

Another area between layout planning and scheduling with a significant influence on energy characteristics, is process planning. In process planning, the sequence of operations of single jobs is determined. Jin and Zhang (2019) investigate this problem using a weighted sum approach to minimise both total production time and energy consumption with the help of an energy consumption coefficient matrix. The test cases from real manufacturing environments show that an average of 40 % of energy consumption reduction can be achieved by including process planning in the scheduling decision.

Going further into the details of the processes themselves, production settings with tool-using machines allow for more influence on the energy characteristics of the final schedule. The selection and actual usage of this tooling can be determined by optimisation. Chen et al. (2019b) integrate cutting tool selection and parameter optimisation in the context of the process planning of a mill. They present a multi-objective approach to minimise energy footprint and total production time. Results show that, as expected, both objectives are conflicting and the integrated approach allows for larger energy footprint savings than solving both problems separately.

When it comes to energy-oriented layout planning, transportation activities can strongly influence energy consumption. Therefore, integrating routing decisions may lead to improved results. The great impact of process and tool characteristics shows that these decisions should not be neglected in practice. Nevertheless, this research stream is strongly focused on energy consumption as the main variable. Hence, time-varying prices are still a promising open research field.

2.5.3 Assembly line balancing

The balancing of assembly lines (and disassembly lines) is an issue that is closely related to the problems of production scheduling and, thus, has been integrated in several papers due to its great influence on the energy consumption of production processes.

Zhang et al. (2020) propose a balancing and sequencing problem for mixed-model assembly lines, typically found in car manufacturing. The authors develop a bi-objective mathematical model minimising energy consumption as well as optimising the balance rate horizontally (workload on each station) and vertically (deviations of workload between stations). Specifically, processing and non-processing energy demands are analysed. The model is solved using a multi-objective algorithm that integrates a cellular strategy and local search. Results show that the energy consumption can be reduced by adjusting the task assignment and model sequence without changing the configuration of the line, while the energy consumption of idle machines has a significant impact on results.

Desta et al. (2018) take a closer look at situations in which utilities impose power limitations. The authors suggest to maximise the production rates for an asynchronous assembly line system while maintaining the performance constraints. They propose a temporal deterministic finite station machine concept, where each state represents machine status (working/idle) and transitions capture temporal changes. A near-optimal schedule is selected by first finding extreme schedules, either by minimising power demand, or by maximising production rates. Then, a constrained local search heuristic is used to find near-optimal schedules by selecting the optimal set of state transitions. The model is tested on a real case in the food industry. Results show that production rates can be increased by up to 70 %, along with an increase in the total energy consumption. However, power limitations are not violated in demand response event times.

Wang et al. (2020b) propose a disassembly line balancing model for waste electronic equipment. They account for uncertainties, but only related to the quality of disassembly parts. The multi-objective model optimises the number of stations, smoothness index (difference in workstation load), energy consumption, and disassembly profit. The problem is solved by a genetic algorithm based on task precedence relationships. One of the main goals is to decide which part has to go through a destructive disassembly process, leading to differences in energy consumption. The analysis of pareto fronts shows that partial disassembly can simultaneously yield higher profits and lower energy consumption.

In assembly line balancing works, the focus still remains strongly on energy consumption. Time-varying pricing schemes are rarely examined, especially, since the associated fluctuating processes may be in strong conflict with the traditional balancing objectives. A further open research field is the integration of more complex energy systems, including on-site generation as well as storage and/or electricity storage, which, in combination, may partially solve conflicts between both varying prices and balancing lines. When analysing energy-aware assembly line balancing, future research should additionally account for the fact that idle times and non-processing energy demands have a significant impact on energy profiles.

2.5.4 Dynamics and rescheduling

Dynamic machining environments are characterised by unexpected, sudden events (e.g., breakdowns, job cancellations) that affect the originally determined deterministic schedule. In order to minimise the overall impact on the schedule itself (i.e., delays), rescheduling has to be performed.

The work of Salido et al. (2017) deals with dynamic changes within a job shop environment, which make rescheduling techniques necessary. Given an unexpected machine disruption affecting the current schedule, machine-specific speed levels are used to recover the original schedule until a so-called ‘match-up point’ is reached. The aims are to maintain the makespan as well as to minimise the energy consumption. In response to uncertain and dynamically changing machine states, rescheduling of production jobs is also initiated in Feng et al. (2020). Unlike common approaches, the authors make use of machine learning techniques allowing to monitor and evaluate the current machine state. In case of necessary adjustments, the findings are promptly posted to the underlying multi-objective optimisation model such that an updated schedule can be determined.

Nouiri et al. (2019) combine an energy-aware flexible job shop problem with an inventory problem. The core element relies on synchronising machining operations with the underlying multi-stage supply chain network with transports. Here, the minimisation of energy consumption and transportation costs (and hence the carbon footprint) are of particular interest. In order to quickly react on sudden unexpected events (e.g., machine breakdowns, arrival of new jobs), rescheduling measures are carried out, allowing to modify the previously determined machine allocations as well as routing decisions.

The discussed papers strongly focus on machine-related, sudden disturbances. Against the background of energy-aware scheduling with respect to fast changing real-time electricity prices, future research could also direct rescheduling activities to the dynamics observed at electricity spot markets. In this context, a disturbance is associated with an unexpected change in the electricity price. So far, machine learning techniques are rarely considered within this stream. However, an integration of these techniques into decision making might be useful, especially, when scheduling is based on predicted electricity prices.

2.5.5 Multiple forms of energy

A number of papers also deals with the integration of multiple forms of energy, where the different forms of energy are convertible from one form into another, e.g., from electricity into heat. The integration of multiple forms of energy is crucial to address the overall energy required within industrial production systems. Besides, it allows to consider energy efficiency on a broader scale.

Dababneh et al. (2016) investigate the control of a heating ventilation and air cooling (HVAC) system in combination with a sequential flow shop. The authors develop a process model that allows to determine electrical power consumption of the HVAC based on the demand for heating respectively cooling to maintain the room temperature of the shop floor within a certain range. In doing so, external temperatures as well as heat emissions from producing machines, convection, and radiation are also considered. The decisions to be made include the heating and cooling state of the HVAC, the use of electrical energy, as well as the manufacturing state of machines. The corresponding model is formulated as a MIP and solved using standard solvers.

Golpîra et al. (2018) investigate energy-oriented lot sizing in a production system which requires electrical as well as thermal energy. For both types of energy, on-site generation and storage technologies are in place, accompanied by an external electricity grid. The transformation of energy is considered with respect to capacities and efficiencies. Since on-site energy generation by wind power as well as the overall heat demand are uncertain, a robust mixed-integer non-linear program is developed in order to determine production quantities and sequences, energy flows, and inventories. The approach takes RTP as well as CPP schemes into consideration and uses a conditional value at risk-technique to examine trade-offs between scenario-based cost deviations and power imbalances with regard to the decision maker's attitude towards risk. The problem is linearised and solved by a standard solver for small-scale problem instances using deterministic scenarios for uncertain parameters.

Biel and Glock (2016a) focus on lot sizing in a two-stage flow shop system producing one product. Both stages require electricity, partially coming from the external grid. More importantly, both stages generate waste heat that can be converted into electricity by an organic rankine cycle. For the energy conversion, the authors propose a mathematical formulation based on a thermodynamic process model, where energy generation is a function of lot sizes, production speeds of both stages, and the number of shipments between stages. The formulation is embedded into a flow shop lot sizing problem and an optimal solution algorithm is proposed. To apply the algorithm, problem instances following a real-world company from the manufacturing sector are extended by realistic technological characteristics for the organic rankine cycle. The instances are solved for different interrupted and continuous production lot strategies, identifying significant cost-related benefits of waste heat recovery.

The discussed papers provide approaches to integrate electricity and heat as important forms of energy in industry. They strongly focus on technologically sound models with clearly distinguishable conversion processes. Nevertheless, the field of multiple energy forms still is a mostly open topic in decision support. Future research could focus on other forms of energy being important for industry like pressurised air or chemical energy. Moreover, approaches to model the technologies of conversion processes are possible open research areas.

2.5.6 Integration of transportation processes

Several authors identified that an integration of transportation issues with production related scheduling decisions seems reasonable from a holistic environmental viewpoint. The subsequently discussed publications can be distinguished by the kind of transport process being integrated in production management in order to leverage further reaching energy-savings potentials.

Hemmati Far et al. (2019) consider a setting with flexible manufacturing cells, where industrial robots conduct production operations while AGVs are responsible for the transportation of material between a storage area and the robots. The authors examine this setting in deterministic as well as fuzzy environments under TOU electricity prices. The optimisation problem involves AGV job allocation decisions and accounts for the corresponding power consumption of moving AGVs within the shop floor. By linking production planning and transportation, the authors contribute a more realistic model formulation with practical relevance. The proposed MIP model minimises the total cost of the production and transportation system as well as the total tardiness of jobs against given job due dates. The results indicate that the proposed algorithms generate high quality solutions. In the line of thought of integrating material handling units into production management, Liu et al. (2019c) integrate crane operations with job shop scheduling. Especially in traditional heavy-duty industrial manufacturing environments, energy consumption of crane equipment can account for a significant amount of the overall energy consumption. The particular environment considered in this paper is a flexible job shop with an overhead gantry crane that transports workpieces between various machines. A corresponding MIP model is presented that decides about the operations of the involved equipment while minimising the total cost of energy consumed by machines and the crane. As the proposed problem is NP-hard, a combination of a genetic algorithm and a swarm heuristic is proposed for its solution. The approach is tested using a real-world case study of a large cement equipment company in China. The company produces industrial assets such as rotary kilns, vertical mills, or roll squeezers. Numerical results for this case study reveal that the algorithm is capable of obtaining high quality solutions in reasonable time. The case study emphasises the approach's practical relevance.

A further expansion of the transportation sphere is investigated in Wang et al. (2019a). This paper combines scheduling decisions of a single manufacturing machine with a vehicle routing problem for the distribution of the finished products to the actual customer locations. This combination seems reasonable, as in the considered setting, customer orders have a due date which needs to be met through a combination of sufficiently short lead times for production and final delivery. In other words, if production decisions affect a late finishing of a product unit, a fast delivery process may still ensure a timely delivery and vice versa. The objective of the proposed optimisation model is to minimise the total carbon emissions resulting from the energy consumption of the production equipment as well as from the fuel consumption of delivery trucks. Hence, it integrates enhanced output-related criteria into the model formulation; see ORC in Table 2.4. As the problem proves to be NP-hard, a tabu search hybrid algorithm is proposed for its solution. The results show that the integrated production scheduling and distribution method is capable of reducing the total CO_2 emissions.

The mentioned articles provide a sound basis for fruitful future research. In particular, it appears promising to systematically extend the system boundaries of production systems towards distribution processes in order to evaluate the environmental performance of production-distribution systems as a whole. What is missing in the literature so far is to include charging decisions of material handling equipment into the production scheduling. Especially the usage of AGVs raises the question, what capabilities these vehicles have and how to fit their recharging into the scheduling of machines that depend on this material handling equipment. Using the batteries of such equipment for (intermediate) storage of energy could be a further innovative aspect of energy-aware operations management. Finally, a systematic approach to the inclusion of various material handling equipment types (e.g., AGVs, portal cranes, conveyor systems, fork lifts, external trucks) and their particularities within production scheduling could put an environmental perspective not only in operational planning, but also in more tactical decisions like a coordinated selection of material handling technology and production technology.

2.6 Conclusions

This literature review has put focus on papers that bring issues of sustainable energy generation, storage, and consumption into operational production planning problems. For this purpose, we conducted a systematic literature search and selection that identified almost 200 relevant articles published between 2016 and 2020. In order to analyse this research systematically, we have proposed a multi-dimensional classification scheme that accounts for novel attributes of energy supply, demand, and storage, next to more classical attributes like the type of production planning problem under investigation, the features of the proposed optimisation model, and the type of the solution method being used. This scheme is applied to clearly reveal the features of the relevant papers and to analyse this body of literature systematically.

Next to a thorough presentation of studies in their respective areas of job scheduling in various machine environments and lot sizing, we provide a detailed analysis of current streams of research. For this purpose, we actively take up and discuss areas of future research mentioned in earlier review papers and we present six research streams that can be found in the recent literature. For each of these streams, we discuss those papers that already contributed to them so far and we identify related topics of future research. With these contributions, we hope that this survey supports the further advancement of energy-aware decision making in production environments. Mentioned in previous surveys, but not yet integrated into the literature, is an event-driven demand response and a realistic modelling of greenhouse gas emissions.

Acknowledgments

This work was supported by the Gesellschaft für Energie und Klimaschutz Schleswig-Holstein GmbH (EKSH) in form of a PhD scholarship for Sebastian Scholz.

2.7 Appendix A: Classification of relevant articles

Table 2.5: Literature classification i.

	Abedi et al. (2020)	Absi et al. (2016)	Aghelinejad et al. (2018)	Ameri Sianaki et al. (2018)	Asghar et al. (2019)	Basso et al. (2019)	Batista Abikarram et al. (2019)	Biel and Glock (2016a)	Biel et al. (2018)	Carrasco et al. (2018)	Che et al. (2016)	Che et al. (2017a)	Che et al. (2017b)	Chen et al. (2019a)	Chen et al. (2019b)	Cheng et al. (2017)	Cheng et al. (2018)	Coca et al. (2019)	Cui et al. (2019a)	Cui et al. (2019b)	Dababneh et al. (2016)	Dai et al. (2019)	Desta et al. (2018)	Ding et al. (2016a)	Ding et al. (2016b)	Ebrahimi et al. (2020)	Ebrahimzadeh Pilerood et al. (2018)	Faccio et al. (2019)	Fang et al. (2016)	Faraji Amiri and Behnamian (2020)	Fazli Khalaf and Wang (2018)	Feng et al. (2020)
Energy supply																																
Generation																																
Grid (off-site)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Adjustable (on-site)								x																								
Non-adjustable (on-site)						x			x										x												x	
Coordination mechanism																																
Time-of-use (TOU)			x	x			x		x		x		x			x	x		x	x					x		x		x			
Critical peak pricing (CPP)																																
Real-time pricing (RTP)						x	x			x							x								x						x	
Load curve penalties (LCP)																							x									
Fixed price		x			x			x						x																		
Energy demand																																
Processing energy demand	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Non-processing energy demand			x		x			x				x			x	x		x	x	x	x	x	x	x		x	x	x		x		
Energy storage																																
P2P						x													x												x	
P2X																																
P2X2P																																
Objective criterion																																
Monetary																																
Energy costs			x		x	x	x	x	x	x	x		x	x		x	x		x	x					x	x	x		x		x	
Peak power costs																			x													
Environmental costs		x						x																								
Production-related costs		x			x			x		x																						x
Inventory costs		x			x			x																								
Tardiness costs						x								x												x						
Other costs					x			x																								
Non-monetary																																
Energy consumption	x											x			x							x		x				x		x		x
Peak power																					x		x									
Environmental																		x						x								
Time-based	x								x	x		x			x	x		x		x		x		x				x		x		x
Production quantity-based				x																			x									
Others																																x
System of objectives																																
Single-objective		x	x		x	x	x	x			x		x	x			x		x		x				x	x	x		x		x	
Multi-objective	x			x					x	x		x			x	x		x		x		x	x	x				x		x		x
Manufacturing model																																
Single machine			x							x	x	x		x		x				x									x			
Parallel machines				x			x						x				x								x			x				
Flow shop								x	x										x		x			x			x			x	x	
Job shop	x																	x				x				x						
Lot sizing		x			x			x																								
Other energy-intensive processes						x									x						x		x			x						x
Mode characteristics																																
Single mode			x	x		x		x	x		x	x		x		x	x	x	x	x	x	x			x			x	x	x	x	
Multi mode	x	x	x		x		x			x			x		x								x	x		x	x		x			
Planning horizon																																
Short-term ($\leq 24\,\text{h}$)			x	x		x	x		x				x		x	x					x	x		x	x	x	x	x	x	x	x	
Mid-term ($> 24\,\text{h}$)			x			x	x				x	x							x													
Long-term (weeks/months)											x																					
Not specified	x	x			x			x		x				x			x	x		x			x									x
Model type																																
LP				x																												
MIP	x	x				x	x	x	x	x	x	x	x			x	x	x		x		x		x	x		x			x	x	x
MINLP														x	x				x		x					x		x				
QT & Simulation																																
Stochastic model					x				x										x											x	x	
Not explicitly presented			x		x																		x						x			
Solution method																																
Heuristic	x		x			x			x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x		x		x		x
Exact algorithm				x	x			x																			x		x			
Exact (solver)		x				x	x	x	x		x	x		x		x	x			x					x		x				x	

Table 2.6: Literature classification ii.

	Foumani and Smith-Miles (2019)	Fu et al. (2019)	Gajic et al. (2017)	Giglio et al. (2017)	Golari et al. (2017)	Golpîra et al. (2018)	Gong et al. (2016)	Gong et al. (2017)	Gong et al. (2018)	Gong et al. (2019)	Gong et al. (2020)	Habibi Tostani et al. (2020)	Hajej and Rezg (2019)	Hemmati Far et al. (2019)	Ho et al. (2020)	Hong et al. (2016)	Iqbal and Al-Ghamdi (2018)	Islam et al. (2018)	Jia et al. (2016)	Jia et al. (2019)	Jia et al. (2020)	Jiang and Deng (2018)	Jiang and Wang (2019)	Jiang et al. (2019)	Jin and Zhang (2019)	Kemmoe et al. (2017)	Kong et al. (2020a)	Kong et al. (2020b)	Lamba et al. (2019)	Lee et al. (2017)	Lei et al. (2017)	Lei et al. (2018)
Energy supply																																
Generation																																
Grid (off-site)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Adjustable (on-site)						x												x														
Non-adjustable (on-site)					x	x																										
Coordination mechanism																																
Time-of-use (TOU)			x				x			x				x	x			x														
Critical peak pricing (CPP)																																
Real-time pricing (RTP)						x	x	x		x																				x		
Load curve penalties (LCP)			x			x																										
Fixed price													x														x	x				
Energy demand																																
Processing energy demand	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x
Non-processing energy demand	x	x		x			x	x		x			x	x			x					x	x	x			x		x	x	x	x
Energy storage																																
P2P						x																										
P2X																																
P2X2P						x																										
Objective criterion																																
Monetary																																
Energy costs			x	x	x	x	x	x		x			x	x	x			x						x			x	x		x		
Peak power costs													x																			
Environmental costs	x													x		x																
Production-related costs				x	x	x		x	x	x	x		x	x		x		x									x		x			
Inventory costs				x	x	x						x	x			x																
Tardiness costs				x	x									x										x						x		
Other costs				x	x	x																						x				
Non-monetary																																
Energy consumption		x							x		x	x					x		x	x	x	x	x		x		x		x		x	x
Peak power																																
Environmental	x								x		x																					
Time-based	x	x							x	x	x	x		x						x	x	x	x		x	x	x					x
Production quantity-based										x																					x	
Others																																
System of objectives																																
Single-objective			x	x	x	x	x	x					x		x	x	x	x	x			x		x		x		x		x		
Multi-objective	x	x							x	x	x	x		x						x	x		x		x		x		x		x	x
Manufacturing model																																
Single machine							x	x																						x		
Parallel machines				x									x							x	x						x	x				x
Flow shop	x	x	x								x				x			x	x				x				x					x
Job shop						x			x	x							x					x		x		x					x	
Lot sizing				x		x							x			x																
Other energy-intensive processes					x							x		x											x				x			
Mode characteristics																																
Single mode			x		x	x	x	x		x		x	x	x			x	x	x				x					x	x	x		
Multi mode	x	x		x					x		x				x	x				x	x	x		x	x	x	x				x	x
Planning horizon																																
Short-term ($\leq 24\,\mathrm{h}$)	x	x		x		x	x		x	x	x						x	x					x	x			x			x		
Mid-term ($> 24\,\mathrm{h}$)			x					x																								
Long-term (weeks/months)					x								x			x																
Not specified												x		x	x				x	x	x	x			x	x		x	x		x	x
Model type																																
LP					x																											
MIP	x	x	x	x		x	x	x		x	x			x	x	x				x	x	x	x			x	x					
MINLP									x			x	x				x	x						x	x				x	x		
QT & Simulation										x									x													
Stochastic model		x			x	x	x							x																		
Not explicitly presented																												x			x	x
Solution method																																
Heuristic		x	x	x	x		x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Exact algorithm																x																
Exact (solver)	x					x							x													x			x			

Table 2.7: Literature classification iii.

	Li et al. (2016)	Li et al. (2017a)	Li et al. (2017b)	Li et al. (2017c)	Li et al. (2017d)	Li et al. (2018a)	Li et al. (2018b)	Li et al. (2018c)	Li et al. (2019)	Li et al. (2020)	Liang et al. (2019)	Liu (2016)	Liu et al. (2016)	Liu et al. (2017b)	Liu et al. (2017a)	Liu et al. (2019a)	Liu et al. (2019b)	Liu et al. (2019c)	Liu et al. (2019d)	Liu et al. (2020a)	Liu et al. (2020b)	Lu and Jiang (2019)	Lu et al. (2016)	Lu et al. (2017)	Lu et al. (2018)	Lu et al. (2019)	Luo et al. (2019)	Mansouri and Aktas (2016)	Mansouri et al. (2016)	Masmoudi et al. (2017b)	Masmoudi et al. (2017a)	Masmoudi et al. (2019)
Energy supply																																
Generation																																
Grid (off-site)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Adjustable (on-site)																																
Non-adjustable (on-site)												x																				
Coordination mechanism																																
Time-of-use (TOU)																				x										x	x	x
Critical peak pricing (CPP)																															x	
Real-time pricing (RTP)																																
Load curve penalties (LCP)																																
Fixed price	x	x									x					x		x				x										
Energy demand																																
Processing energy demand	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Non-processing energy demand	x	x	x	x	x		x	x	x	x			x	x	x	x		x		x	x	x	x	x	x	x	x	x	x	x	x	
Energy storage																																
P2P												x																				
P2X																																
P2X2P																																
Objective criterion																																
Monetary																																
Energy costs	x	x									x					x		x		x		x				x	x			x	x	x
Peak power costs																														x	x	
Environmental costs																																
Production-related costs		x									x					x			x							x				x	x	
Inventory costs											x																			x	x	
Tardiness costs	x																x		x			x					x					
Other costs																																
Non-monetary																																
Energy consumption		x	x	x	x	x	x	x	x	x			x	x	x		x		x		x		x	x	x		x	x	x			
Peak power																														x		
Environmental												x													x							
Time-based			x				x	x	x	x		x	x	x		x		x	x	x	x			x	x		x	x	x			
Production quantity-based				x		x			x																							
Others																							x									
System of objectives																																
Single-objective	x				x						x			x	x							x				x				x	x	x
Multi-objective		x	x	x		x	x	x	x	x		x	x			x	x	x	x	x	x		x	x	x		x	x	x			
Manufacturing model																																
Single machine		x	x	x								x				x	x						x									
Parallel machines	x																															
Flow shop						x	x	x			x			x	x					x	x			x	x			x	x	x	x	
Job shop									x	x			x					x				x				x	x					x
Lot sizing																														x	x	
Other energy-intensive processes					x													x	x													
Mode characteristics																																
Single mode	x						x	x			x	x	x	x		x	x	x		x					x					x	x	x
Multi mode		x	x	x		x			x	x					x				x		x	x	x	x		x	x	x	x			
Planning horizon																																
Short-term ($\leq 24\,\mathrm{h}$)			x					x		x					x			x						x	x					x	x	x
Mid-term ($> 24\,\mathrm{h}$)						x						x	x		x														x			
Long-term (weeks/months)																			x													
Not specified	x	x		x	x		x		x		x			x		x	x			x	x	x	x			x	x	x				
Model type																																
LP						x																										
MIP	x	x		x				x			x	x		x	x	x		x	x	x				x		x		x	x	x	x	x
MINLP			x																						x		x					
QT & Simulation						x																										
Stochastic model														x																		
Not explicitly presented					x		x		x	x			x				x				x	x	x									
Solution method																																
Heuristic	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Exact algorithm																																
Exact (solver)											x	x						x										x	x		x	

Table 2.8: Literature classification iv.

	Meng et al. (2019c)	Meng et al. (2019a)	Meng et al. (2019b)	Modarres and Izadpanahi (2016)	Módos et al. (2017)	Mokhtari and Hasani (2017)	Nouiri et al. (2019)	Nujoom et al. (2019)	Öztop et al. (2020)	Pan et al. (2019)	Peng et al. (2018)	Perković et al. (2017)	Pham et al. (2019)	Plitsos et al. (2017)	Puttkammer et al. (2016)	Ramezanian et al. (2019)	Ramos and Leal (2017)	Rapine et al. (2018b)	Rapine et al. (2018a)	Rocholl et al. (2020)	Rodoplu et al. (2019)	Rubaiee and Yildirim (2019)	Rubaiee et al. (2019)	Ruiz Duarte et al. (2020)	Saberi-Aliabad et al. (2020)	Safarzadeh and Niaki (2019)	Salido et al. (2016)	Salido et al. (2017)	Schulz et al. (2019)	Schulz et al. (2020)	Shi et al. (2019)	Sin and Chung (2020)
Energy supply																																
Generation																																
Grid (off-site)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Adjustable (on-site)												x												x								
Non-adjustable (on-site)												x	x											x								
Coordination mechanism																																
Time-of-use (TOU)										x							x			x	x	x	x	x	x					x		x
Critical peak pricing (CPP)																																
Real-time pricing (RTP)																													x			
Load curve penalties (LCP)				x	x					x											x			x								
Fixed price						x						x	x		x											x					x	
Energy demand																																
Processing energy demand	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Non-processing energy demand	x	x	x				x	x	x		x	x	x	x		x		x	x		x	x									x	x
Energy storage																																
P2P													x											x								
P2X												x					x															
P2X2P																																
Objective criterion																																
Monetary																																
Energy costs				x		x				x		x			x		x			x	x	x	x	x	x	x			x	x		x
Peak power costs																					x											
Environmental costs																																
Production-related costs				x				x					x		x			x	x		x			x								
Inventory costs				x				x					x					x	x		x			x								
Tardiness costs											x																					
Other costs				x								x	x						x													
Non-monetary																																
Energy consumption	x	x	x				x	x	x		x			x		x											x	x			x	
Peak power																													x			
Environmental				x				x																							x	
Time-based					x	x	x		x					x		x				x		x	x			x	x	x	x	x	x	x
Production quantity-based																																
Others																																
System of objectives																																
Single-objective	x	x	x		x					x			x		x		x	x	x		x			x	x							
Multi-objective				x		x	x	x	x		x	x		x		x				x		x	x			x	x	x	x	x	x	x
Manufacturing model																																
Single machine					x										x		x					x	x									x
Parallel machines			x											x				x	x	x					x	x			x			
Flow shop			x						x	x	x					x					x			x					x	x	x	
Job shop	x	x				x	x					x		x													x	x				
Lot sizing																		x	x	x	x											
Other energy-intensive processes				x			x	x				x	x																			
Mode characteristics																																
Single mode		x	x	x	x		x	x			x		x	x	x		x	x	x	x	x	x	x	x	x				x		x	x
Multi mode	x					x			x	x						x										x	x	x		x		
Planning horizon																																
Short-term ($\leq 24\,\mathrm{h}$)					x		x			x					x					x		x	x	x				x	x		x	
Mid-term ($> 24\,\mathrm{h}$)							x														x											
Long-term (weeks/months)				x				x				x	x	x			x															
Not specified	x	x	x			x			x		x					x		x	x						x	x	x			x		x
Model type																																
LP																																
MIP	x	x	x	x	x	x	x		x		x	x	x		x	x	x	x	x	x	x	x	x	x	x	x			x	x	x	
MINLP								x		x																						x
QT & Simulation							x							x																	x	
Stochastic model													x																			
Not explicitly presented																											x	x				
Solution method																																
Heuristic	x		x		x	x	x	x	x	x	x	x		x	x	x		x	x	x	x	x	x		x	x	x	x	x		x	x
Exact algorithm					x													x	x					x								
Exact (solver)	x	x	x	x			x		x				x				x					x	x		x					x		

Table 2.9: Literature classification v.

	Sinha and Chaturvedi (2018)	Soleimani et al. (2020)	Su et al. (2017)	Tan et al. (2018)	Tan et al. (2019)	Tang et al. (2016)	van den Dooren et al. (2017)	Wang (2019)	Wang and Wang (2019)	Wang et al. (2016)	Wang et al. (2018a)	Wang et al. (2018b)	Wang et al. (2018c)	Wang et al. (2018d)	Wang et al. (2019a)	Wang et al. (2019b)	Wang et al. (2020a)	Wang et al. (2020b)	Wang et al. (2020c)	Weitzel and Glock (2019)	Wichmann et al. (2019a)	Wichmann et al. (2019b)	Wu and Che (2019a)	Wu and Che (2019b)	Wu and Sun (2018)	Wu et al. (2018a)	Wu et al. (2018b)	Wu et al. (2019a)	Wu et al. (2019b)	Wu et al. (2020)	Xu et al. (2018)	Yan and Zheng (2020)
Energy supply																																
Generation																																
Grid (off-site)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Adjustable (on-site)					x																											
Non-adjustable (on-site)																				x		x					x					
Coordination mechanism																																
Time-of-use (TOU)				x	x					x				x		x												x			x	
Critical peak pricing (CPP)																																
Real-time pricing (RTP)																					x	x										
Load curve penalties (LCP)				x																x												
Fixed price			x				x								x		x															
Energy demand																																
Processing energy demand	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Non-processing energy demand				x		x	x				x	x		x	x		x		x	x	x	x	x		x	x	x		x	x	x	x
Energy storage																																
P2P																				x		x					x					
P2X																																
P2X2P																																
Objective criterion																																
Monetary																																
Energy costs				x	x		x			x				x	x	x				x	x	x						x			x	
Peak power costs																																
Environmental costs					x			x																								
Production-related costs												x						x			x	x				x					x	
Inventory costs																					x	x				x						
Tardiness costs																																
Other costs				x	x			x													x					x						
Non-monetary																																
Energy consumption	x	x				x					x	x	x				x	x	x				x	x	x				x	x		x
Peak power																																
Environmental	x		x												x												x				x	
Time-based		x				x			x	x	x		x			x	x		x	x			x	x	x		x	x		x	x	
Production quantity-based																	x	x														
Others																									x				x			
System of objectives																																
Single-objective	x		x	x	x		x	x	x					x	x						x	x				x						x
Multi-objective		x				x				x	x	x	x		x	x	x	x	x	x			x	x	x		x	x	x	x	x	
Manufacturing model																																
Single machine	x									x					x													x				
Parallel machines		x		x			x						x	x		x								x		x						
Flow shop			x			x		x	x		x		x	x		x				x			x				x			x	x	x
Job shop												x					x								x				x			
Lot sizing				x																	x	x				x						
Other energy-intensive processes					x										x			x	x													
Mode characteristics																																
Single mode	x	x	x				x				x	x	x	x	x	x	x		x	x	x	x				x		x				
Multi mode				x	x	x		x	x	x													x	x	x		x		x	x	x	x
Planning horizon																																
Short-term ($\leq 24\,h$)				x	x					x			x	x	x	x			x	x	x	x								x	x	
Mid-term ($> 24\,h$)								x									x	x									x					
Long-term (weeks/months)			x																													
Not specified	x	x					x		x		x	x											x	x	x	x		x	x			x
Model type																																
LP																																
MIP		x	x	x	x	x	x		x	x			x	x		x	x	x	x	x	x	x	x	x		x		x				
MINLP												x			x										x		x		x	x	x	x
QT & Simulation																	x															
Stochastic model																																
Not explicitly presented	x							x			x																					
Solution method																																
Heuristic	x	x	x			x	x	x	x	x	x	x	x	x	x	x	x	x	x				x	x	x	x	x	x	x	x	x	
Exact algorithm								x																								x
Exact (solver)				x	x		x		x	x			x			x				x	x	x				x						

Table 2.10: Literature classification vi.

	Yan et al. (2016)	Yang et al. (2018)	Yin et al. (2016)	Yüksel et al. (2020)	Zandi et al. (2019)	Zeng et al. (2018a)	Zeng et al. (2018b)	Zeng et al. (2018c)	Zhang and Chiong (2016)	Zhang and Jiang (2019)	Zhang et al. (2016a)	Zhang et al. (2016b)	Zhang et al. (2017a)	Zhang et al. (2017b)	Zhang et al. (2017c)	Zhang et al. (2018a)	Zhang et al. (2018b)	Zhang et al. (2018c)	Zhang et al. (2018d)	Zhang et al. (2019a)	Zhang et al. (2019b)	Zhang et al. (2019c)	Zhang et al. (2019d)	Zhang et al. (2019e)	Zhang et al. (2020)	Zhao et al. (2018)	Zheng and Wang (2018)	Zheng et al. (2019)	Zhou and Shen (2018)	Zhou et al. (2018)	Zhou et al. (2019)	Zhu and Tianyu (2019)
Energy supply																																
Generation																																
Grid (off-site)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Adjustable (on-site)																																
Non-adjustable (on-site)																		x														
Coordination mechanism																																
Time-of-use (TOU)		x				x										x	x									x		x		x		
Critical peak pricing (CPP)																		x														
Real-time pricing (RTP)																																
Load curve penalties (LCP)																																
Fixed price							x																									
Energy demand																																
Processing energy demand	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x
Non-processing energy demand	x		x	x			x			x		x	x		x					x			x	x	x		x		x	x	x	x
Energy storage																																
P2P																																
P2X																																
P2X2P																																
Objective criterion																																
Monetary																																
Energy costs		x				x	x									x	x	x								x		x		x		
Peak power costs																																
Environmental costs		x																														
Production-related costs		x								x									x							x						
Inventory costs																																
Tardiness costs																																
Other costs																			x													
Non-monetary																																
Energy consumption	x		x	x	x			x	x	x	x	x	x		x				x	x	x	x	x	x	x				x		x	x
Peak power																																
Environmental								x						x													x					
Time-based	x		x	x	x		x		x	x	x			x	x		x		x	x	x	x		x			x	x	x	x	x	x
Production quantity-based															x																	
Others						x													x						x							
System of objectives																																
Single-objective		x										x	x			x		x				x	x			x						
Multi-objective	x		x	x	x	x	x	x	x	x	x			x	x		x		x	x	x			x	x		x	x	x	x	x	x
Manufacturing model																																
Single machine			x		x					x				x		x	x															
Parallel machines		x				x		x										x		x	x	x					x			x	x	x
Flow shop	x	x		x			x	x										x	x	x	x					x		x			x	
Job shop									x		x	x	x	x	x								x	x								
Lot sizing																																
Other energy-intensive processes												x													x				x			
Mode characteristics																																
Single mode		x					x				x	x	x			x		x	x		x		x	x		x						
Multi mode	x		x	x	x	x		x	x	x		x		x	x		x			x		x			x		x	x	x	x	x	x
Planning horizon																																
Short-term ($\leq 24\,\text{h}$)	x		x		x			x	x	x	x	x		x	x		x		x		x	x	x	x		x		x	x			x
Mid-term ($> 24\,\text{h}$)																x									x		x	x				x
Long-term (weeks/months)						x	x											x														
Not specified		x		x									x							x										x	x	
Model type																																
LP																		x														
MIP	x		x	x	x	x	x	x	x		x	x	x			x	x		x	x	x	x	x	x		x	x	x	x	x		
MINLP													x	x	x			x							x	x						x
QT & Simulation															x																	
Stochastic model		x																														
Not explicitly presented										x																					x	
Solution method																																
Heuristic	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x	x	x	x	x	x
Exact algorithm																																
Exact (solver)		x		x		x					x		x				x									x						

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Chapter 3

Coordination of heterogeneous production equipment under an external signal for sustainable energy

Publication status Published in 2022: *Journal of Cleaner Production* 338: 130461. https://doi.org/10.1016/j.jclepro.2022.130461

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Abstract Increasing yet volatile generation of electricity from renewable energy sources constitutes challenges to prevent grid bottlenecks and to ensure grid stability. Similarly, energy-intensive industrial companies have to take care of their internal power load management to prevent energy infrastructure overloads. We bring these two fields together by (1.) optimizing production scheduling and equipments' charging decisions such that the internal load management of a company is respected while (2.) supporting grid stability through increased local consumption in periods of peak generation of renewable energy. For this, the considered company receives an external signal about the availability of (excessive) renewable energy. We present two optimization models that incorporate this signal when making production and charging decisions for heterogeneous types of equipment. The main objectives consider minimization of total tardiness, maximization of

energy consumption in periods of excessive renewable energy generation and minimization of peak loads. Total job completion time forms a subordinate objective. We further propose a production coordination platform (PCP) that orchestrates the decision making of both optimization models. Computational experiments consider a manufacturing system that consists of two heterogeneous production equipment types with two machines and two support devices and demonstrate that the PCP is competitive compared to an integrated optimization model. It is shown that a hierarchical order of the diverse objectives is properly reflected in the decision making such that a company can flexibly adapt its internal load management to the current situation of renewable energy generation. Sensitivity analyzes of control parameters reveal how the performance of the PCP reacts to different degrees of information availability. We finally show that the signal-driven PCP can achieve a substantial reduction of production-related CO_2 emissions.

Keywords Machine scheduling, charging decision, load management, demand response, grid stability, CO_2 emission

3.1 Introduction

In recent years, a significant increase in generating electricity from renewable energy sources has been achieved, see Capizzi et al. (2019). Temporal fluctuations in renewable energy generation constitute challenges for the stability of power grids. This calls for *feed-in management* to prevent overloads as lacks of grid infrastructure prevent far distance transmission of energy from the locations where this energy is produced to those that face a high energy demand. Far distance energy transmissions constitute a grid bottleneck and wind mills, solar panels etc. may be shut down temporarily to prevent feed-in. Consequently, renewable energy is not generated, although it could have been produced, which constitutes an undesirable loss of sustainable energy. As an example, feed-in management actions caused a loss of 6.48 GWh of renewable energy in Germany in the year 2019 (Bundesnetzagentur 2019).

One approach to reduce feed-in management actions and thus, the loss of sustainable energy, without overloading transmission infrastructure to distant demand places is to *temporarily increase local consumption* of energy in times of peaks in energy generation. This relieves the grid and the potential bottleneck is bypassed. This paper presents a methodology for flexibly adapting the production processes to the availability of excessive sustainable energy. The company receives an *external signal* that indicates for upcoming periods, whether or not feed-in management actions are necessary. The demand side knows through the external signal when to increase its own consumption such that the loss of renewable energy due to feed-in management is reduced.

Pushing energy consumption to relieve the grid and to avoid a loss of renewable energy constitutes a challenge for the *internal load management* of a company. This is because internal peak loads are a thread to a company's factory infrastructure and a substantial component of the energy prices. Thus, grid stabilization by fostering local consumption cannot be considered without a company's internal load management too. The internal load of a company is determined by various, heterogeneous energy consumers like *machines*, *support devices* (e.g., electrified fork lifts for material handling) and others. While energy consumption of machines is determined mostly through *job scheduling decisions*, support devices are subject to *charging decisions*. The latter takes the form of an inventory management that keeps track of a device's charging level. To consider both types of consumers, we present two optimization models, one for making job scheduling decisions of a machine and one for making charging decisions of a support device. Both models take into account the external signal for the availability of renewable energy as well as the internal peak load. As it seems unrealistic to consider the decisions of such heterogeneous consumers within a single, holistic decision making process, we present a *production coordination platform* (PCP). The PCP coordinates the individual decision making processes of these considered equipment types.

The remainder of this paper is organized as follows. Section 3.2 gives an overview of the relevant energy-aware production scheduling literature. Section 3.3 presents the models for the heterogeneous types of equipment, an integrated optimization model as a benchmark and the PCP that coordinates the individual, short-sighted decision making. As the decision making has to trade-off the consumption of renewable energy with service-oriented goals like meeting job due dates, we consider these decision making processes under a set of well defined performance measures. Computational experiments in Section 3.4 analyze the performance of the individual decision making processes and the PCP as a whole and identify to what extend a consideration of the external signal supports eco-friendly production operations. Section 3.5 concludes the paper.

3.2 Literature review

In recent years, energy consideration in the context of production scheduling received a lot of attention in research and is addressed in various research streams under a variety of terms. Following Schulz et al. (2019), we subsume this research under the term 'energy aware scheduling'. Detailed literature overviews of research on energy aware scheduling are provided by Biel and Glock (2016), Gahm et al. (2016) and Bänsch et al. (2021). Renna and Materi (2021) put special emphasis in their review on articles integrating renewable energy sources in manufacturing systems. Energy aware scheduling means that industrial consumers respond to energy price variations or other trigger events by changing their consumption patterns. The subsequent literature review will emphasize three energy aware research streams that differ in the way of considering energy related information. These are: price driven demand response, event driven demand response, and peak power reduction.

Price driven demand response means to take into account varying energy prices when making production decisions. It is primarily considered in terms of time-of-use prices, where high energy prices occur in on-peak periods and low prices in off-peak periods in order to smoothen consumption patterns. While Zhang et al. (2014) investigate a flow shop setting, Shrouf et al. (2014) focus on a single machine production setting under time-of-use tariffs. Che et al. (2017) consider a time-of-use energy tariff within a scheduling problem of unrelated parallel machines to minimize energy costs. Rubaiee and Yildirim (2019) examine a preemptive single-machine scheduling problem with time-of-use energy prices to minimize both, total completion time and total energy cost. Biel et al. (2018) consider a flow shop scheduling problem with stochastic on-site wind power generation under time-of-use energy prices. They minimize the total weighted flow time and expected energy costs. In this line of thought, Subramanyam et al. (2020) develop a two-stage mixed-integer model minimizing the energy costs of a flow shop that is powered by onsite renewable energy plants. The first stage minimizes the annual energy consumption subject to a job throughput requirement. The second stage sizes wind turbines, solar panels and battery units to meet the hourly electricity demand. Wang et al. (2020) present a two-stage multi-objective stochastic optimization model for flow-shop scheduling under a time-of-use electricity pricing scheme additionally integrating on-site renewable energy generation and an energy storage system. Additionally, Materi et al. (2021) propose an approach to reduce energy costs and CO_2 emissions by production system energy flexibility through photovoltaic plant and battery storage integration. In this line of thought, Karimi and Kwon (2021) propose an approach to analyze the effect of energy-aware production scheduling, on-site solar power generation and battery energy storage on energy cost and makespan. Numerical experiments demonstrate the cost-saving and performance effect that results from different configuration settings. Other papers consider critical peak pricing for reflecting energy costs within production scheduling. Critical peak pricing is based on time-of-use tariffs such that energy consumption peaks during critical peak periods are charged with especially high prices. While Bego et al. (2014) propose a demand response program for sustainable manufacturing enterprises to identify reservation capacity, Ashok (2006) introduces a peak load management model to incorporate the characteristics of batch-type loads, which is common in the process industry. Zhang et al. (2018) address the sizing of an on-site generation system and the corresponding production plan of a manufacturing system in order to minimize total energy related cost under critical peak pricing conditions. Yusta et al. (2010) consider real time prices that change (at least) on an hourly basis. The authors aim at finding a production schedule that maximizes the company's profit calculated as the difference between sales income and related production costs, where the latter also include electricity cost.

Contrasting price driven demand response, event driven demand response received much less attention in the literature. In particular, Sun and Li (2014) consider demand response as a reaction to triggering events like local weather change. An automotive assembly line manufacturing system is subject to a throughput-constraint. The goal is to reduce power consumption when triggering events indicate a challenging situation for the power grid or the internal load profile while keeping the throughput constant for the considered work shifts. Beier et al. (2017) propose a method for a real-time energy flexibility control logic to match a manufacturing systems energy demand with renewable energy generation without throughput loss.

Peak power reduction is either considered as a means of internal load management by establishing a hard peak load limit or by considering a minimization of the peak load. A hard limit in terms of a constraint is suggested by Ashok and Banerjee (2001) for a flour mill scheduling problem that minimizes energy costs and by Fang et al. (2013) for a flow shop scheduling problem with makespan-minimization. Masmoudi et al. (2017) contemplate a capacitated flow shop environment where minimizing peak power is part of a cost function. Schulz et al. (2019) contribute a multi-objective mixed-integer program (MIP) model for hybrid flow-shop scheduling with real-time energy prices. The model exhibits three objective functions minimizing makespan, total energy costs, and peak power. Ashok (2006) and Schulz (2018) link the reduction of energy consumption, price driven demand response, and peak power reduction within a single model formulation. Ashok (2006) presents a model that minimizes monthly operating costs regarding energy costs with time dependent energy charges, machine speed variation and charges for the maximum demand. Schulz (2018) contribute a multi-objective MIP model for hybrid flow-shop scheduling with real time energy prices. The three subcategories of energy aware scheduling are addressed in this model through an objective function that minimizes energy consumption and peak power under volatility prices.

The analyzed publications reveal a focus on price driven demand response. Anyhow, to the best of our knowledge, there exists no approach that combines event driven demand response with a reduction of power peaks. To achieve this, we integrate an external signal that indicates availability of excessive renewable energy. Beyond that, the analyzed publications solely consider job scheduling and exclude further production related energy consumers like support devices for material handling. Hence, we approach the heterogeneity of production equipment through corresponding model formulations and propose a production coordination platform that flexibly orchestrates the decision making of this equipment.

3.3 A framework for coordinating heterogeneous production equipment

3.3.1 Production environment and external signal

We consider an industrial company with an heterogeneous production equipment manufacturing environment. The equipment is divided into two general types. The first equipment type refers to machines that have to execute production jobs. The second equipment type are support devices like, for example, electric fork lifts that handle material or air tanks that supply compressed air. While the machines call for job scheduling decisions, support devices have to made charging decisions. The proposed approach can be applied to various kinds of manufacturing environments that involve energy intensive processes such as laser cutting, melting, welding, pressing, material lifting, or others.

Research typically considers production scheduling and charging decisions as isolated problems. From the perspective of a company's internal load management, these kinds of equipment decisions are interdependent as both contribute to the overall energy load profile. We therefore consider a PCP that links the individual decision making of the equipment units. As such, the platform is capable to coordinate different kinds of equipment through their individual decision making models.

The decision making faces the challenge of conflicting objectives between production related goals and energy consumption related goals. With regard to energy consumption, a classical goal is to minimize peak consumption, see e.g. the survey of Bänsch et al. (2021). In order to avoid feed-in management actions a further energy-related goal can be to *maximize consumption* during periods with excessive renewable energy generation. This prevents a loss of renewable energy that could be generated but needs

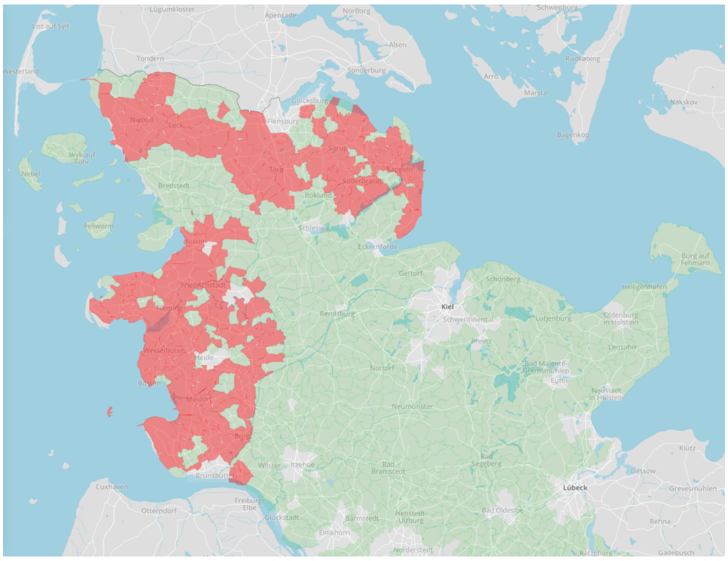

Figure 3.1: 'Netzampel' Schleswig-Holstein, Germany (Schleswig-Holstein Netz AG 2021).

to be suppressed if insufficient current energy consumption exists. In parts of Germany and especially in the federal state of Schleswig-Holstein, the so-called ENKO-Netzampel (Schleswig-Holstein Netz AG 2021) provides information about the availability of renewable energy, see Figure 3.1. It depicts an hourly forecast of feed-in management actions at the community level for up to 24 hours. Red color indicates excessive renewable energy in the municipality and thus, necessary feed-in management. For a local company, such an *external signal red* (*ESR*) indicates that power-intensive operations could be conducted to consume energy that would otherwise be lost. *External signal green* (*ESG*) indicates, that no feed-in management is necessary and thus, no loss of sustainable energy is observed. By considering the external signal an opportunity is given to consume excessive renewable energy in *ESR*-periods and support grid stability.

The existing literature predominantly considers price signals from the energy-market for energy aware scheduling, see discussion in Section 3.2. Price signals support a cost-driven decision making. The price signal merely reflects the market-wide availability of renewable energy. Such price signals therefore cannot support locally driven renewable energy generation and avoidance of feed-in management, at a municipality level. Therefore, we investigate how to include such a signal into a company's operations management.

To investigate the presented production environment and the role of the external signal within the PCP, we present in Subsections 3.3.2 and 3.3.3 individual optimization models for a single machine and a single support device. Subsection 3.3.4 introduces the integrated optimization model serving as a benchmark and 3.3.5 describes the PCP that links the individual equipment model formulations and coordinates the decisions of all machines and support devices in a company's production environment.

3.3.2 Optimization model for scheduling jobs on a machine

We consider a single machine and a set of jobs J that need to be processed on this machine. The decision making is based on discrete time periods. The time horizon of interest is denoted by T and subdivided into time intervals of equal length. This enables aligning the production decisions to the external signal forecast, which follows the same time intervals. The machine can process a single job at a time, job processing is assumed to be non-preemptive and there are no job precedence relations. For each job $j \in J$, a release date r_j and a due date d_j is given, where job j cannot be started before its release date. The machine can operate in different modes S. For processing a job, a machine processing mode $s \in S$ must be chosen. The processing mode s affects the processing speed and implies a trade-off between the processing time $p_{j,s}$ of a job j and the corresponding energy consumption $q_{j,s}$. Further input is given by the load profile lp_t, which is the company's power consumed in period t. We assume that the external signal is given for periods $t \in T$ through a parameter re_t with value $re_t = -1$ for *ESR*-periods and $re_t = 1$ for *ESG*-periods. In *ESR*-periods, the available renewable energy capacity is assumed to be infinite. Finally, a parameter n is given, which defines how many of the jobs of set J the model should schedule in the current planning run. This parameter is later used by the PCP to coordinate the various production equipment.

The decisions to be made are modelled through binary variable $x_{j,s,t}$, which is equal to 1 if processing job j in mode s starts in period t, 0 otherwise. Binary variable $y_{j,s,t}$ is equal to 1 if job j is processed in mode s in period t, 0 otherwise. Continuous variable pl measures the peak energy consumption over the entire planning horizon. The notation is summarized in Table 3.1. The proposed decision support model is then formulated as follows:

The model considers three (partly) conflicting objectives *TA, ES, PL*, see objective functions (3.1a) to (3.1c). The minimization of the total tardiness (*TA* in (3.1a)) constitutes the first objective. Tardiness occurs only if the difference between a jobs completion time and its due date is positive. The corresponding max-function in (3.1a) can be easily linarized using standard techniques. The second objective (*ES* in (3.1b)) represents the external signal objective, which synchronizes production with *ESR*-periods and maxi-

Table 3.1: Notation used for modeling the decision making.

Sets	
J	Set of jobs being released for the machine under consideration
S	Set of processing modes
T	Set of periods
Parameters	
r_j	Release date of job $j \in J$ [period]
d_j	Due date of job j [period]
$p_{j,s}$	Processing time of job j in mode $s \in S$ [periods]
$q_{j,s}$	Power consumed by job j in mode s per period processing time [kW per period]
lp_t	Company's load profile in period t [kW]
re_t	Dichotomous parameter, with $re_t = -1$ if external signal red (*ESR*) indicates feed-in management in period t, otherwise $re_t = 1$ (*ESG*)
n	Number of jobs to be added to schedule
Decision variables	
$x_{j,s,t}$	Binary variable, equal to 1 if processing job j in mode s starts in period t, 0 otherwise
$y_{j,s,t}$	Binary variable, equal to 1 if job j is processed in mode s in period t, 0 otherwise
pl	Peak load, measured as maximum energy demand [kW] over the entire planning horizon

mizes the shift of energy consumption from *ESG*- to *ESR*-periods. The third objective (*PL* in (3.1c)) represents the minimization of peak loads, as many industrial company's are additionally charged for their highest energy peak load. We solve this multi-objective problem hierarchically, i.e., we consider one of these performance measures as primary objective and the others as subordinate objectives, as this enables to distinct the functioning of the different performance measures.

$$\min \rightarrow TA = \sum_{j\in J}\sum_{s\in S}\sum_{t\in T|r_j\leq t} \max\{0, x_{j,s,t}\cdot(t+p_{j,s}-d_j-1)\} \tag{3.1a}$$

$$\min \rightarrow ES = \sum_{j\in J}\sum_{s\in S}\sum_{t\in T|r_j\leq t} y_{j,s,t}\cdot q_{j,s}\cdot re_t \tag{3.1b}$$

$$\min \rightarrow PL = pl \tag{3.1c}$$

$$\sum_{s\in S}\sum_{t\in T|r_j\leq t} x_{j,s,t} \leq 1 \qquad j \in J \tag{3.2}$$

$$\sum_{t\in T} y_{j,s,t} = \sum_{t\in T|r_j\leq t} x_{j,s,t}\cdot p_{j,s} \qquad j \in J, s\in S \tag{3.3}$$

$$\sum_{\tau\in T|t\leq\tau\leq t+p_{j,s}-1} y_{j,s,\tau} \geq\ x_{j,s,t}\cdot p_{j,s} \qquad j \in J, s\in S, t\in T \tag{3.4}$$

$$\sum_{j\in J}\sum_{s\in S}\sum_{t\in T|r_j\leq t} x_{j,s,t} = min\{n, |J|\} \tag{3.5}$$

$$\sum_{j\in J|r_j\leq t}\sum_{s\in S} y_{j,s,t} \leq 1 \qquad t\in T \tag{3.6}$$

$$\sum_{j\in J}\sum_{s\in S} y_{j,s,t}\cdot q_{j,s} + lp_t \leq pl \qquad t\in T \tag{3.7}$$

$$pl \geq 0 \tag{3.8}$$

$$x_{j,s,t}, y_{j,s,t} \in \{0,1\} \qquad j \in J, s\in S, t\in T \tag{3.9}$$

Feasibility of solutions is ensured by the following constraints. Constraints (3.2) ensure that each job j is started at most once after being released. Constraints (3.3) impose job processing times by ensuring that executing job j in mode s takes exactly $p_{j,s}$ periods. Constraints (3.4) guarantee that jobs are processed non-preemptively. Constraint (3.5) ensures that n jobs or less are scheduled in the current planning run depending on the size of job set J. Constraints (3.6) assure that at most one job j is processed by the machine in each time period t. Constraints (3.7) compute the highest peak load pl. While Constraint (3.8) ensures that pl cannot take negative values, (3.9) assures the binary character of variables $x_{j,s,t}$ and $y_{j,s,t}$.

3.3.3 Optimization model for charging decisions of a support device

In this section, we consider a single support device that assists machines in their production operations. Such a device might be an electric forklift that handles material, or an air tank that provides compressed air to the production equipment. Each support device holds an inventory of a resource that is depleted when supporting machine operations. The jobs scheduled on the machines constitute a demand that consumes this inventory of a support device. Considering a particular type of support device, we denote by b_j the amount of the device's inventory that is consumed per period while job j is processed

Table 3.2: Additional notation for charging decisions of support devices.

Sets	
$\widetilde{T}$	Set of look ahead horizon periods $\widetilde{T} \subseteq T$
Parameters	
inv_0	Initial inventory of support device
inv_{max}	Maximum inventory of support devise
de_t	Demand faced by support device in period $t \in T$
ϕ_t	Equal to 1 if support device faces demand in period t (i.e. $de_t > 0$), 0 otherwise
q_s	Power consumed per period charging in mode s [kW per period]
c_s	Charging amount per period in mode s
scc	Equal to 1 if support device can charge and consume simultaneously, 0 otherwise
Decision variables	
$z_{s,t}$	Binary variable, 1 if support device charges in mode s in period t, 0 otherwise
inv_t	Dependent continuous variable stating the inventory at the end of period t

on a machine. From the job scheduling decisions $y_{j,s,t}$ of all machines being active in a period t, we can derive a total demand de_t faced by the considered support device in period t. Whether or not the support device faces such a demand in period t is indicated by binary parameter ϕ_t, which is equal to 1 if $de_t > 0$ and 0 otherwise.

The support devices inventory recharging consumes energy and needs to be aligned with the machines' production operations, which is why we present an optimization model that covers the charging decisions of a support device. For this, we denote by $\widetilde{T}$ a subset of the entire period set T for which charging decision are to be made. This set characterizes the support device's look ahead horizon for making charging decisions. It is derived from the periods the machines have completed their decision making for. An initial inventory level is given by inv_0 and inventory is restricted by a limit inv_{max}. The inventory is reduced in period t by demand rate de_t. The support device can recharge in different processing modes S. The modes $s \in S$ differ by the charge rate c_s and the power consumption q_s per period. The charge rate expresses the energy charged to the battery for a forklift whereas it expresses the added amount of compressed air for the air tank, etc. The availability of different modes S allows to trade-off the charge speed versus the energy that is consumed per period of charging. Whether a support device is capable to charge and fulfill demand simultaneously within a same period is denoted by binary parameter scc. As an example, while an air tank can be refilled and provide pressured air to machines at the same time ($scc = 1$), an electric forklift cannot charge and handle material simultaneously ($scc = 0$). The charging decision for the support device is then modelled through the binary decision variable z_{st}, which is equal to 1 if the device charges in mode $s \in S$ in period $t \in \widetilde{T}$. The dependent continuous variable inv_t keeps track of the resulting inventory. Table 3.2 summarizes the additional notation that is introduced for this model. The optimization model for the charging decisions of the support device is then as follows:

$$\min \rightarrow TA = \sum_{s \in S} \sum_{t \in \widetilde{T}} z_{s,t} \cdot t \tag{3.10a}$$

$$\min \rightarrow ES = \sum_{s \in S} \sum_{t \in \widetilde{T}} z_{s,t} \cdot q_s \cdot re_t \tag{3.10b}$$

$$\min \rightarrow PL = pl \tag{3.10c}$$

$$\sum_{s \in S} z_{s,t} \leq 1 \qquad t \in \widetilde{T} \tag{3.11}$$

$$inv_t = inv_{t-1} - de_t + \sum_{s \in S} z_{s,t} \cdot c_s \qquad t \in \widetilde{T} \tag{3.12}$$

$$\sum_{s \in S} z_{s,t} + \phi_t \leq 1 + scc \qquad t \in \widetilde{T} \tag{3.13}$$

$$\sum_{s \in S} z_{s,t} \cdot q_s + lp_t \leq pl \qquad t \in \widetilde{T} \tag{3.14}$$

$$0 \leq inv_t \leq inv_{max} \qquad t \in \widetilde{T} \tag{3.15}$$

$$pl \geq 0 \tag{3.16}$$

$$z_{s,t} \in \{0, 1\} \qquad s \in S, t \in \widetilde{T} \tag{3.17}$$

The model involves three objective functions, which strive for similar goals as the machine scheduling objectives (3.1a) - (3.1c). In particular, the first objective (TA in (3.10a)) reflects a time goal for early support device loading, which ensures sufficient inventory and avoids job tardiness on machines due to insufficient support device inventory. The second objective (ES in (3.10b)) represents the external signal objective that synchronizes charging with ESR-periods. The third objective (PL in (3.10c)) represents the minimization of peak loads. Feasibility of the support device's charging decisions is ensured by Constraints (3.11) to (3.17). Constraints (3.11) assure that at most one charge mode can be chosen for a period. Constraints (3.12) compute the inventory inv_t

at the end of period t taking into account the inventory inv_{t-1} at the end of the previous period, the demand de_t in the current period and the charge $z_{s,t} \cdot c_s$. Constraints (3.13) assure that those devices that are capable of simultaneous charging and demand fulfillment ($scc = 1$) can do both in a period whereas other devices ($scc = 0$) either charge or fulfill demand in a period. Constraints (3.14) compute the maximum peak load pl, similar to Constraints (3.7) in the job scheduling model. Constraints (3.15) ensure the non-negativity of inventory and respects the inventory's upper limit. Constraint (3.16) assures non-negativity of variable pl while Constraints (3.17) assure the binary character of variables $z_{s,t}$.

3.3.4 Integrated optimization model

The individual models for machines and support devices of Sections 3.3.2 and 3.3.3 will be coordinated by a Production Coordination Platform (PCP) that is explained in Section 3.3.5. As a benchmark for the platform's decentral decision making, we present here an integrated optimization model (IOM) that solves the decisions jointly for a set of machines M and a set of support devices SD in a centralized manner. Please note that it seems unrealistic to apply such a holistic optimization model in practice for a production setting with many heterogeneous types of equipment due to the required coordination of all involved decision makers. Therefore, the IOM solely serves as a theoretical benchmark for the PCP. The notation used for this model is summarized in Table 3.3. The IOM model is then defined by (3.18a) - (3.31). The objective functions (3.18a) - (3.18c) merge the objective functions (3.1a) - (3.1c) and (3.10a) - (3.10c). Constraints (3.19) - (3.31) reflect Constraints (3.2) - (3.9) and (3.11) - (3.17) but for the cases of a set of machines M and a set of support devices SD, respectively.

$$
\begin{aligned}
\min \rightarrow TA = \; & \sum_{m \in M} \sum_{j \in J_m} \sum_{s \in S} \sum_{t \in T | r_{j,m} \leq t} \max\{0, x_{j,m,s,t} \cdot (t + p_{j,m,s} - d_{j,m} - 1)\} \\
& + \sum_{sd \in SD} \sum_{s \in S} \sum_{t \in T} z_{sd,s,t} \cdot t && \text{(3.18a)} \\
\min \rightarrow ES = \; & \sum_{m \in M} \sum_{j \in J_m} \sum_{s \in S} \sum_{t \in T | r_{j,m} \leq t} y_{j,m,s,t} \cdot q_{j,m,s} \cdot re_t \\
& + \sum_{sd \in SD} \sum_{s \in S} \sum_{t \in T} z_{sd,s,t} \cdot q_{sd,s} \cdot re_t && \text{(3.18b)} \\
\min \rightarrow PL = \; & pl && \text{(3.18c)}
\end{aligned}
$$

Table 3.3: Notation used for the IOM.

Sets	
M	Set of machines
J_m	Set of jobs to be processed on machine $m \in M$
SD	Set of support devices
S	Set of processing modes
T	Set of periods
Parameters	
$r_{j,m}$	Release date of job j for machine m [period]
$d_{j,m}$	Due date of job j for machine m [period]
$p_{j,m,s}$	Processing time of job j for machine m in mode s [periods]
$b_{j,m,sd}$	Support device sd inventory needed for processing job j on machine m
$q_{j,m,s}$	Power consumed by job j for machine m in mode s [kW per period]
$c_{sd,s}$	Charging amount per period of support device sd in mode s
scc_{sd}	Equal to 1 if support device sd is capable to charge and consume simultaneously, 0 otherwise
$q_{sd,s}$	Power consumed per period by support device sd charging in mode s [kW per period]
lp_t	Company's load profile in period $t \in T$ [kW]
re_t	Dichotomous parameter, with $re_t = -1$ if external signal red (ESR) indicates feed-in management action in period t, otherwise $re_t = 1$ (ESG)
$bigM$	Sufficiently large positive number
Decision variables	
$x_{j,m,s,t}$	Binary variable, equal to 1 if processing job j on machine m in mode s starts in period t, 0 otherwise
$y_{j,m,s,t}$	Binary variable, equal to 1 if job j on machine m is processed in mode s in period t, 0 otherwise
$z_{sd,s,t}$	Binary variable, equal to 1 if support device sd charges in mode s in period t, 0 otherwise
$\phi_{sd,t}$	Binary variable, equal to 1 if support device sd faces demand in period t, 0 otherwise
$inv_{sd,t}$	Dependent continuous variable stating the inventory of support device sd at the end of period t
$de_{sd,t}$	Dependent continuous variable stating the demand faced by support device sd in period t
pl	Peak load, measured as maximum energy demand over the entire planning horizon [kW]

$$\sum_{s \in S} \sum_{t \in T | r_j \leq t} x_{j,m,s,t} = 1 \qquad m \in M, j \in J_m \tag{3.19}$$

$$\sum_{t \in T} y_{j,m,s,t} = \sum_{t \in T | r_j \leq t} x_{j,m,s,t} \cdot p_{j,m,s} \qquad m \in M, j \in J_m, s \in S \tag{3.20}$$

$$\sum_{\tau \in T | t \leq \tau \leq t + p_{j,m,s} - 1} y_{j,m,s,\tau} \geq x_{j,m,s,t} \cdot p_{j,m,s} \qquad m \in M, j \in J_m \; s \in S, t \in T \tag{3.21}$$

$$\sum_{m \in M} \sum_{j \in J_m | r_j \leq t} \sum_{s \in S} x_{j,m,s,t} \cdot b_{j,m,sd} = de_{sd,t} \qquad sd \in SD, t \in T \tag{3.22}$$

$$\sum_{j \in J_m | r_j \leq t} \sum_{s \in S} y_{j,m,s,t} \leq 1 \qquad m \in M, t \in T \tag{3.23}$$

$$\sum_{m \in M} \sum_{j \in J_m} \sum_{s \in S} y_{j,m,s,t} \cdot q_{j,m,s} + \sum_{sd \in SD} \sum_{s \in S} z_{sd,s,t} \cdot q_{sd,s} + lp_t \leq pl \qquad t \in T \tag{3.24}$$

$$\sum_{s \in S} z_{sd,s,t} \leq 1 \qquad sd \in SD, t \in T \tag{3.25}$$

$$\sum_{s \in S} z_{sd,s,t} + \phi_{sd,t} \leq scc_{sd} + 1 \qquad sd \in SD, t \in T \tag{3.26}$$

$$inv_{sd,t} = inv_{sd,t-1} - de_{sd,t} + \sum_{s \in S} z_{sd,s,t} \cdot c_{sd,s} \qquad sd \in SD, t \in T \tag{3.27}$$

$$de_{sd,t} \leq \phi_{sd,t} \cdot bigM \qquad sd \in SD, t \in T \tag{3.28}$$

$$0 \leq inv_{sd,t} \leq inv_{max} \qquad sd \in SD, t \in T \tag{3.29}$$

$$pl \geq 0 \tag{3.30}$$

$$x_{j,m,s,t}, y_{j,m,s,t}, z_{sd,s,t}, \phi_{sd,t} \in \{0,1\} \qquad m \in M, j \in J_m, s \in S, \; sd \in SD, t \in T \tag{3.31}$$

3.3.5 Production coordination platform

To combine the introduced model formulations for machines (3.3.2) and support devices (3.3.3) in a flexible manner, we conceptualize a Production Coordination Platform (PCP). The PCP does not make decisions itself but calls the respective decision making model of an equipment unit. In this way, it coordinates the decisions and is capable to orchestrate multiple units of heterogeneous types of equipment.

Clearly, an autonomized PCP requires means of information exchange among equipment units, which can be established nowadays through machine-to-machine (M2M) communication (Verma et al. 2016). The decision making of machines and support devices is then performed on the PCP-server through *smart agents* that hold the individual optimization models of machines and support devices. Following the definition of an intelligent agent of Wooldridge (2002), a smart agent is understood as a computer program that executes rules and specified processes that are triggered autonomously. The PCP keeps track of the state of the production system (in particular the load profile resulting from the decisions made), receives triggering signals from equipment units, calls smart agents for making decisions, and sends the decisions made to the equipment units. The platform incrementally builds a schedule for production and charging processes over time. By introducing control parameters (number of jobs n to schedule on a machine, look ahead horizon $\widetilde{T}$ for charging decisions of support devices) the decision making is subdivided along the overall horizon. We assume that information forecasts are more certain when applying a shorter planning horizon and uncertainty of input data becomes negligible.

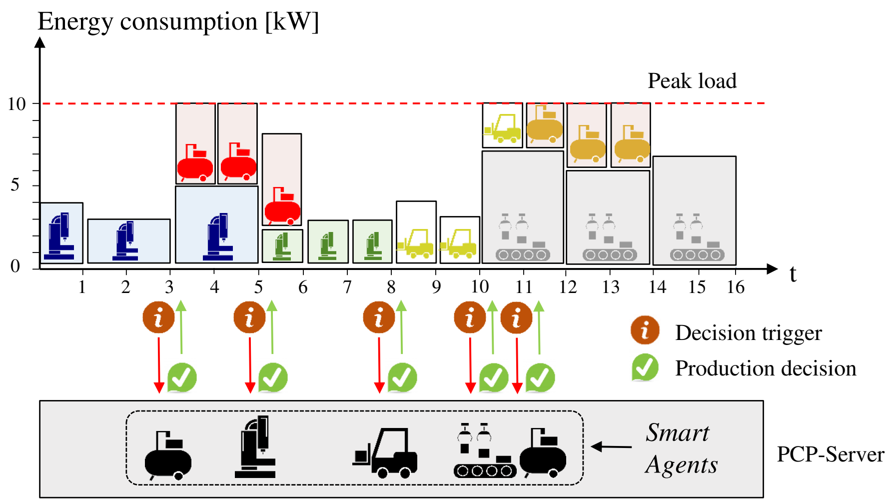

Figure 3.2: Conceptual sketch of the PCP.

Figure 3.2 visualizes the functioning of the PCP. The figure shows the load profile (energy consumption) of the overall production system in the course of time. The boxes represent production processes of machines and charging processes of support devices where the width represents processing time and the height corresponds to the energy consumption. Boxes stacked upon one another add up to the overall load profile. In this PCP illustration, the machine control parameter n is set to $n = 3$. This effects that a machine schedules three further jobs each time it runs idle and its smart agent is triggered to perform a planning run. Boxes with same color indicate that the corresponding processes result from the same planning run.

The operational functioning of the PCP is then as follows. Upon receiving a triggering event for a production equipment unit, the platform calls the corresponding smart agent to make the required decisions. Events for triggering a decision making process are:

- a new job is released
- an equipment unit is running idle
- a support device's inventory cannot meet a future demand

With the focus on the *smart agent* level, each equipment icon symbolizes the incrementally developing operations plan of the company, which emerges from the planning runs of the triggered agents. The PCP provides all required information to the smart agents (e.g., job set J for a machine, or demand rates de_t for a support device). With our energy-oriented focus, the PCP provides the load profile lp_t, which comprises the energy consumption per period, to the smart agent. As this profile follows from all those decisions that other smart agents made before, the currently triggered agent respects these decisions when solving its own optimization model. The PCP is aware of the external signal re_t of upcoming periods. Once a smart agent solved its optimization model, the resulting instructions (expressed through decision variables $x_{j,s,t}$, $y_{j,s,t}$, $z_{s,t}$) are communicated to the respective equipment unit directly or to its operator and the platform updates relevant information like the company's load profile lp_t, job set J, demands for support devices de_t, or inventory levels inv_t at the PCP-server for being available for future decision making.

To illustrate the functioning of the PCP, we take up Figure 3.2 and turn it into a (numerical) example. In the beginning, only the blue operations are scheduled from a previous planning run of the considered machine. This effects a load profile of 4, 3, 3, 5, 5 kW in the first five periods, with a peak of 5 kW. The machine runs idle at time 5, which triggers the corresponding smart agent on the PCP to schedule further jobs. We assume $n = 3$ jobs for this decision making and the newly scheduled three jobs appear in green in the figure. They keep the machine busy until time 8. At that time, the machine runs idle again. We assume that there are no further jobs available at that time and, thus, the machine stays idle. Furthermore, the first support device's smart agent (red pressure tank) is triggered at time 3 due to insufficient inventory. It makes charging decisions for the next three periods, which contribute to the load profile. The forklift's smart agent is triggered at time 8 to meet further support device demand. It charges till time 11.

With new jobs being released at time 10, the second machine, which was idle so far, is now triggered and schedules $n = 3$ jobs for the upcoming six periods. The pressure tank recharges from 11 to 14 (orange icons) to meet the support device demand of machine 2. The resulting overall load profile lp_t has a peak load of 10 kW.

For our subsequent experiments, we simulate the behaviour of such a PCP through the processes that are sketched in the flowchart of Figure 3.3. This simulations handles a priority queue of triggering events that occur on the PCP. The priority queue yields the next trigger event on the PCP according to the time at which they occur, see process (4). Then, the platform identifies the equipment type (machine or support device) (decision

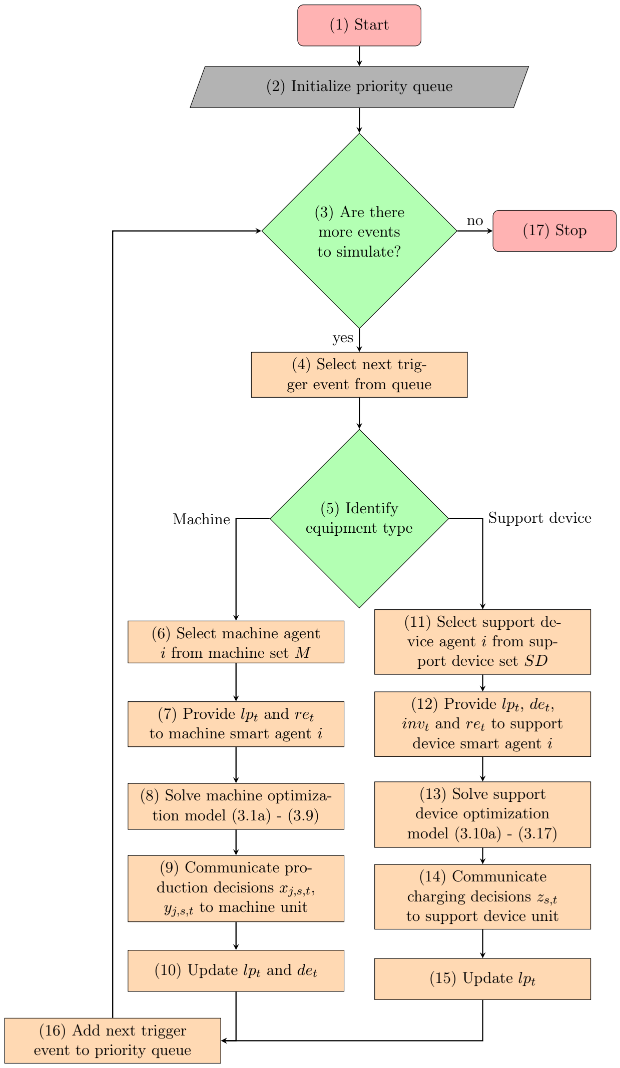

Figure 3.3: PCP simulation framework flowchart.

(5)) and selects the particular agent i that corresponds to the piece of equipment that triggered the request (process (6) or (11)). The agent receives the necessary information (process (7) or (12)), which includes (among others), the current load profile lp_t that reflects the energy demand of those operations that were planned through earlier decision-making processes of machines and support devices. The agent then solves its optimization model (process (8) or (13)). The results of the optimization are communicated to the corresponding piece of equipment that executes the newly planned operations, which are either the jobs scheduled on a machine (process (9)) or the charging decisions of a support device (process (14)). The load profile lp_t and the demand rates de_t are then updated to take into account the energy demand of the newly planned operations (processes (10), (15)). If appropriate, a follow-up request is added to the priority queue (process (16)), for example to trigger a machine's smart agent again as soon as the considered machine processed all jobs that were scheduled in the current planning run.

3.4 Computational study

3.4.1 Computational study setup

To evaluate the proposed approach and its intended effectiveness by integrating excessive renewable energy and load management into production decision making, we conduct the following computational study. The findings are applicable for a variety of similar industrial manufacturing environments. Our study is built around a manufacturing system that consists of two heterogeneous production equipment types with two machines and two support devices each. Each machine has to process 50 jobs within a 300 period planning horizon while the support devices need to meet demand for this horizon. Over this horizon, the support devices have to fulfill the demands that arise from the production decisions. Each period corresponds to 15 minutes, which fits the typical time interval at which electricity companies identify peak loads in energy demand. The 300 period planning horizon regarding 15 minutes per period thus equals 75 hours. As the Netzampel's forecast of the external signal covers a horizon of 24 hours only, progressive decision making as is established by the PCP becomes essential to take into account forecast updates in a rolling horizon fashion. Each job $j \in J$ can be processed in one out of three processing modes, i.e., $|S| = 3$. Job processing times $p_{j,s}$ are measured in periods and drawn from the uniform distribution U[1,6] such that processing times differ for the three processing modes. Rates $q_{j,s}$ reflect the different power consumptions of these modes. There exists a trade-off between processing time and power consumption such that a decrease in processing time by choosing a processing mode of higher processing speed comes along with an increase in power consumption. Job release dates r_j follow a uniform distribution U[1,150] and the corresponding due dates d_j are calculated as $r_j + 150$. As support devices, we consider one electric forklift and one air pressure tank. The forklift's inventory consumption b_j for supporting machine job j is drawn from the range [1,8] as is derived from ISO 23308-1 (ISO 2020). For the air tank, consumption rate b_j is drawn from a similar range [0,6], where the lower bound is 0 as not all jobs require pressured air for their processing. The PCP computes the resulting demand rates de_t. Both support devices exhibit three charging modes S. The devices differ in power consumption q_s and charge rates c_s for mode $s \in S$. They also differ in their capability of simultaneous charging and fulfilling demand. For this, the compressed air tank is capable to charge and serve simultaneously ($scc = 1$), while the forklift can either charge or fulfill demand ($scc = 0$). The data of the external signal is derived from Schleswig-Holsteins feed-in management actions in 2019 corresponding to approximately 80% *ESR*-period occurrence and accounts for different scenarios of *ESR*-period occurrences. All test data generated for this study is available at the repository [https://www.scm.bwl.uni-kiel.de/de/forschung/research-data].

All computations are performed on an Intel Core i7 with a 3.6 GHz CPU and 32 GB memory. For solving the optimization models, we use the MIP solver CPLEX 12.9.0. The PCP has been implemented in Python 3.7 using the libraries *queue, pandas, numpy and doopl.factory.*

3.4.2 Comparison of PCP and an integrated optimization model (IOM)

As the original data set does not gain solutions for the IOM and all objectives within 48h, we scale down the data set from Section 3.4.1 in this experiment to the first 25 jobs and 150 periods and adjust release and due dates accordingly. Control parameter n is not considered in the IOM, as this benchmark assumes perfect and complete information to be given. Consequently, a look ahead horizon $\widetilde{T}$ is not involved, as it equals horizon T.

In the following comparison, we solve the considered problem using the PCP and the IOM for the pure objectives *TA*, *ES*, and *PL*. For a fair comparison, the PCP-control parameter n accounts for the entire job set of the down-scaled data set ($n = 25$). For the obtained solutions, we analyze the following key performance indicators (KPI) that are derived from the multiple objectives: the total job tardiness (*TA* machines) respectively total support device completion time (*TA* support devices), which corresponds to the *TA*-objectives in each of the model formulations, the energy consumption during *ESR*-

Table 3.4: Comparison of IOM and PCP.

Objective →	*TA*		*ES*		*PL*	
KPI ↓	IOM	PCP	IOM	PCP	IOM	PCP
TA machines [period]	**0**	**0**	147	265	148	361
TA support devices [period]	**37**	**37**	2,943	3,182	1,678	711
ESR-periods [kWh]	3,124	3,185	**5,159**	**5,159**	2,292	2,292
ESG-periods [kWh]	810	832	**0**	**0**	646	647
PL [kW]	369	376	501	417	**105**	**110**
Computation time [sec.]	37	8	88	4	2,231	216

and *ESG*-periods, which are derived from the *ES*-objectives in the models, and the peak load (*PL*) that constitutes the third objective function in the two models.

and the computation times for IOM and PCP under each considered objective are reported in Table 3.4. Those KPIs that refer to the primary objective are shown in bold font. Considering job tardiness and support device completion time minimization (objective *TA*), the PCP and the IOM both yield comparable solutions with almost all KPIs being nearly identical. Both approaches are capable to avoid job tardiness and shift support device charging to early periods. Regarding the *ES*-objective, both PCP and IOM achieve that the total energy consumption occurs entirely in *ESR*-periods but

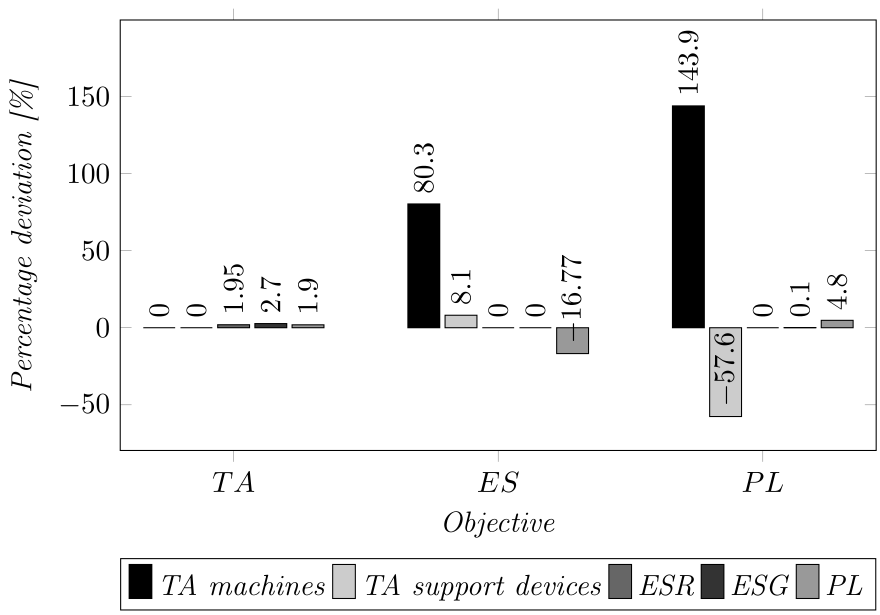

Figure 3.4: PCP KPI variation compared to IOM solution.

at the cost of higher *TA* as well as *PL*, compared to the previous setting. Forcing the production system to support the power grid's stability by an utmost consumption in *ESR*-periods comes along with a substantially higher total consumption of about 30%. As this renewable energy would otherwise be lost, this higher energy consumption does not constitute an environmental concern. As this solution focuses on the external signal, the schedule exhibits job tardiness for machines and support device activities that span up the whole planning horizon, which is reflected by high values of '*TA* machines' and '*TA* support devices'. Finally, under the *PL*-objective, the PCP and the IOM are both successful in reducing peak loads compared to objective *TA* and *ES*, but at the cost of even higher *TA* values for the machines and also more energy consumption in *ESG*-periods. The IOM performs slightly better and is capable to reduce *PL* by further 5 kWh.

In this experiment, we observe that the PCP delivers (almost) identical values for the considered objective as the IOM if it is given perfect information too and is capable to reduce computation times significantly. Figure 3.4 reports the percentage deviation of the PCP KPIs compared to the IOM solution. Solutions with due date violations might be considered unacceptable from the customer perspective. Differences only occur in the subordinate KPIs. We observe that the IOM and the PCP can achieve solutions of good service quality (e.g., for the *TA*-objective) and of good environmental performance (all other objectives). The PCP's decentral decision making is able to keep up with an IOM under the given conditions. Building up on this, the following experiments will examine the impact of limited information-availability (i.e., varied PCP-control parameter) in Subsection 3.4.3 and objective combinations as well as of different external signal scenarios in Subsection 3.4.4 on the PCP's performance.

3.4.3 Varying control parameter

In the previous experiment, the computations were based on PCP-control parameter n covering the entire job set and the entire planning horizon representing perfect and complete information. This allowed to plan all operations within a single equipment's planning run. In this subsection, we analyze the role of this parameter. The lower the value of the control parameter, the more the decision making is subdivided along the overall horizon. The smart agents are triggered more often but schedule a reduced number of jobs and fewer charging decisions per planning run. Such settings become relevant if information about jobs, corresponding support device demands, or signal forecasts are partly uncertain and vary over time such that perfect information is no longer available.

We analyze here to what extend this effects the solutions. We again consider the three objectives *TA*, *ES*, and *PL* and vary the control parameter n systematically over the complete range [1,50]. For the extremely small value $n = 1$, a triggered smart agent of a machine schedules just a single job whereas the extreme value $n = 50$ covers the whole job set like in the previous experiment. The periods $\widetilde{T}$ for which the support devices can make their decisions depends on the periods for which machines have already planned production operations. This adapts the look ahead of the charging decisions to the job scheduling of the machines, as is reasonable if the platform faces incomplete information due to dynamically arriving jobs or changes in the (forecasted) external signal.

Note, that a low value of n might effect that not all the jobs in set J are served within the given time horizon T. This is because the few jobs that are to be scheduled in a planning run might be placed late within the planning horizon, depending on the chosen objective. From this, the next triggering of the corresponding machine agent takes place late in the planning horizon, from which remaining jobs might run out of time and cannot be inserted within the residual periods. Consequently, we introduce a further KPI, the so-called *service level* (*SL*), which expresses the number of jobs that the PCP can include into the solution. Since our tests involve two machines with 50 jobs each, the maximum value of *SL* is 100 jobs, respectively 100 %. A maximization of this KPI is achieved by adding *SL* to the objective function and by adapting Constraint (3.5).

We start by solving the problem under the pure objective *TA*. The corresponding service level under varied values of n is shown by the dashed curve in Figure 3.5. It

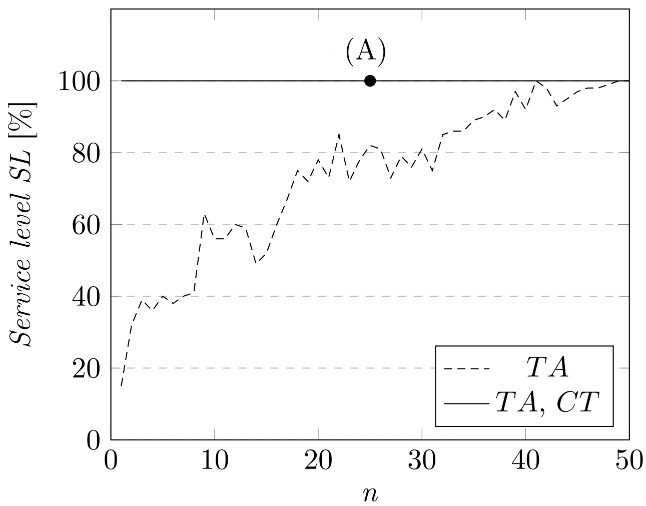

Figure 3.5: Service level with varied control parameter n for objective *TA*.

Table 3.5: Solutions for $n = 25$ under various objectives.

KPI ↓ / Objective →	*TA*, *CT* (A)	*ES*, *CT* (B)	*PL*, *CT* (C)
TA machines [period]	**0**	204	2,354
TA support devices [period]	**2,424**	7,381	5,152
ESR-periods [kWh]	8,381	**11,085**	6,559
ESG-periods [kWh]	2,110	**0**	1,297
PL [kW]	553	519	**260**
Computation time [sec.]	55	46	450

can be seen that for $n = 1$ only 15 out of the 100 jobs are scheduled. For $n = 20$ we achieve a service level of about 80 %. The poor performance with respect to *SL* can be improved significantly by establishing *total job completion time* (*CT*) as a secondary objective. This prioritizes scheduling jobs with early due dates and avoids unused gaps in a production schedule. The solid line in figure 3.5 demonstrates that considering *CT* as a secondary objective yields a perfect service level where the PCP can schedule 100 % of the jobs. For the moderate control parameter of $n = 25$ (point (A) in the figure), Table 3.5 provides the corresponding KPI values and the computation time. It can be seen that combining *TA* and *CT* as primary and secondary objectives achieves that jobs are processed without tardiness.

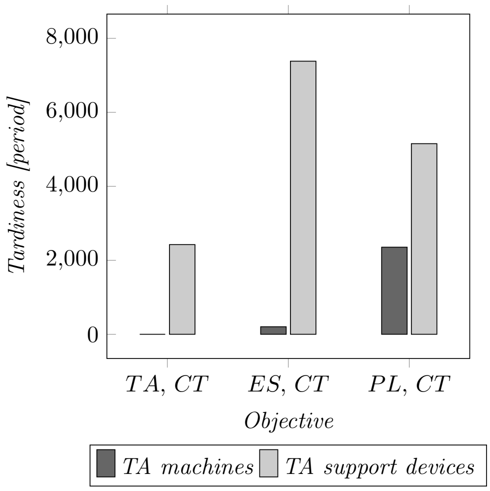

Figure 3.6: Tardiness under various objectives.

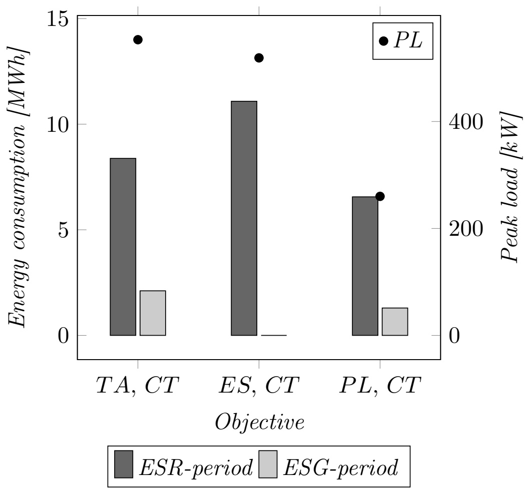

Figure 3.7: Energy consumption and peak load under various objectives.

Service levels for the exclusive objective *ES* are shown by the dashed line in Figure 3.8. For $n = 1$ only 17 out of the 100 jobs are scheduled. This is due to the strict focus on aligning production with the external signal. With $n = 1$, a single job is scheduled in each planning run and this job is placed within the next sequence of successive *ESR*-periods that fits to the job's processing time. This means that previous *ESG*-periods, but also smaller sequences of *ESR*-periods, are skipped and lost for scheduling other jobs in later planning runs as the smart agents advance through time. The PCP does not perform well with regards to *SL* if it is too restricted in the number of jobs to schedule and if the focus is strictly on the external signal. In turn, *SL* improves for larger values of n but reaches its maximum only for $n = 50$. Like before, considering *CT* as secondary objective improves the service level significantly, see solid line in Figure 3.8. Here, apart from $n = 1$ and $n = 2$ with SLs of 95 % and 93 % all further values of the control parameter achieve a *SL* of 100 %. For the moderate control parameter of $n = 25$ (point (B) in the figure), Table 3.5 again provides the corresponding KPI. For this setting the entire production takes place during *ESR*-periods.

Figure 3.9 depicts the results of varying n with regard to objective *PL* by the dashed line and with regard to a combination of *PL* and *CT* by the solid line. Here, the pure objective *PL* again exhibits a poor *SL* that rises only slowly. Incorporating *CT* as a secondary objective again improves the *SL* drastically, although a service level of 100 % can be achieved only for $n = 50$. For $n = 25$, a near optimal service level is achieved for which the corresponding KPIs are again provided in Table 3.5. The different KPI values dependent on the objective are illustrated in Figures 3.6 and 3.7.

This experiment demonstrated the influence of control parameter variations that

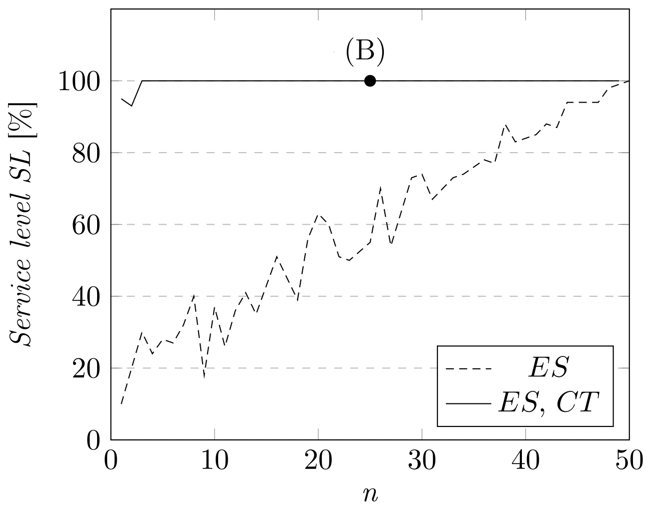

Figure 3.8: Service level with varied control parameter n for objective *ES*.

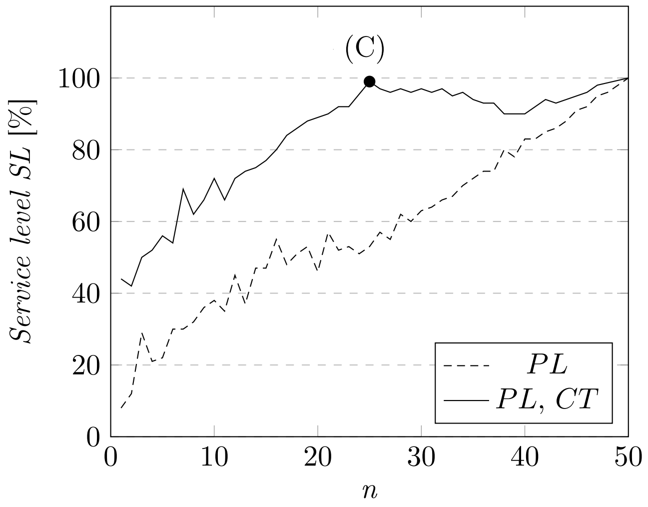

Figure 3.9: Service level with varied control parameter n for objective PL.

reflect different degrees of information availability on the obtained PCP solutions, where solution quality is measured in terms of a service level next to other KPIs. All solutions exhibit a higher SL when integrating CT minimization as a secondary objective, which is why we keep CT as secondary objective in the further experiments. From integrating this objective, the immanent conflict among a company's goal of high service quality and environmental performance can be traded off in the decision making of the PCP. This finding leads to the conclusion that integrating CT as a secondary objective in the PCP's decentral decision making is advisable to improve solution quality.

3.4.4 Objective combinations and external signal scenarios

In this section, we will focus on four further objective combinations under a moderate control parameter ($n = 25$). These objective combinations include a tertiary objective. Combination TA, CT, PL is a corporate-oriented hierarchy of service- and load-management objectives. Combination ES, CT, TA gives priority to the environmental goal without losing sight of service quality. Combination PL, CT, ES tries to maximize the consumption of renewable energy under the primary objective of minimizing peak loads. Finally, PL_{ESG}, CT, ES follows a similar idea but the peak load is measured only for ESG-periods to further incentivize companies in consuming energy in ESR-periods. While the previous computations were based on just one forecast scenario of the external signal, we will also investigate the influence of alternative signal scenarios. Through this, we finally quantify the achieved saving of CO_2 from consuming energy in ESR- instead

Table 3.6: Solutions for $n = 25$ under various objective combinations.

KPI ↓ / Objective →	TA, CT, PL	ES, CT, TA	PL, CT, ES	PL_{ESG}, CT, ES
TA machines [period]	**0**	**131**	1,482	0
TA support devices [period]	**2,424**	**5,544**	8,197	5,613
ESR-periods [kWh]	8,242	**11,085**	**6,493**	**11,085**
ESG-periods [kWh]	2,170	**0**	**1,161**	**0**
PL [kW]	**523**	553	**260**	**0**
PL in *ESR*-periods [kW]	-	-	260	510
PL in *ESG*-periods [kW]	-	-	248	0
Computation time [sec.]	302	192	1,594	277

of *ESG*-periods.

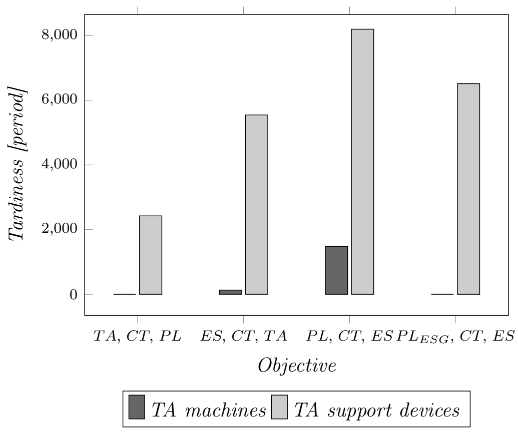

Figure 3.10: Tardiness under various objective combinations.

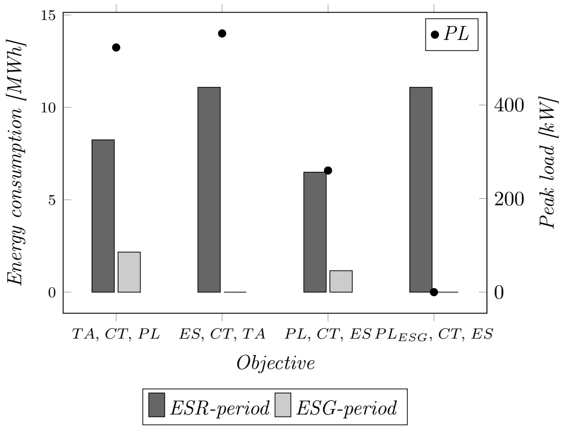

Figure 3.11: Energy consumption and peak load under various objective combinations.

As an extension to *TA* as primary and *CT* as secondary objective ((A) in Figure 3.5 and Table 3.5) we first add peak load reduction (*PL*) as tertiary objective. This setting corresponds closest to a company's corporate goals as it aims at job tardiness avoidance to satisfy customer needs and additional peak load reduction to flatten the internal load curve and reduce energy related costs. Column '*TA, CT, PL*' in Table 3.6 shows the corresponding KPI values incorporating the additional tertiary objective. Contrasting '*TA, CT*' (Table 3.5) with '*TA, CT, PL*' (Table 3.6), the peak load is further reduced from 553 to 523 (about 5 %). The additional peak load objective improves the internal load management while the primary objective of minimizing job tardiness is kept at the same level.

Under an environmental primary perspective, a relevant objective combination is to additionally consider *TA* as a tertiary objective next to *ES* as primary and *CT* as secondary objective. Thus, the external signal synchronisation of objective *ES* is supplemented by job tardiness avoidance. Comparison of the KPIs of column '*ES, CT*' in Table 3.5 with '*ES, CT, TA*' in Table 3.6 reveals that *TA* values can be further reduced by about 36 % for machines and 25 % for support devices under constant *ESR*- and *ESG*-period energy consumption.

At the moment, companies might be more interested in their internal load management, rather than in aligning production decisions with the external signal. Objective combination *PL*, *CT*, *ES* respects this but tries to shift energy consumption into *ESR*-periods provided that the peak load is kept at a minimum. Corresponding KPIs are shown in column 'PL, CT, ES' in Table 3.6. Compared to '*PL, CT*' in Table 3.5, we observe that the consumption in *ESG*- and *ESR*-periods is hardly changed from this tertiary objective. One reason for this is that the peak load is identified over all *ESG*- and *ESR*-periods such that companies do not have a strong incentive for shifting energy consumption into *ESR*-periods. To overcome this disincentive, it could be helpful if energy suppliers identify peak load solely from *ESG*-periods so that high energy consumption in *ESR*-periods is possible without compromising *PL* goals. Objective combination PL_{ESG}, CT, ES takes this into account by solely considering *ESG*-periods for computing the peak load. The right column in Table 3.6 confirms that such a change gives a strong incentive for consuming energy in *ESR*-periods, where all consumption takes place in these times. Clearly, such a strict solution is only possible if *ESR*-periods constitute a substantial amount of the overall planning horizon, which is the case with 80 % such periods in the external signal scenario considered here. The different KPI values of the various objective combinations are illustrated in Figures 3.10 and 3.11.

We finally investigate the role of alternative scenarios for the external signal to examine the impact of different intensities of feed-in management actions and the resulting environmental effects. The monthly frequency of feed-in management actions in the federal state of Schleswig-Holstein, Germany, in 2019 provides the data foundation for these scenarios. The average *ESR*-period occurrence in this year was about 80 %, which constituted the data basis for all previous experiments. We refer to this external signal scenario as ESS_{80}. Two further scenarios (ESS_{75}, ESS_{85}) are generated by adjusting the status quo of 80 % by +/-5 % *ESR*-period occurrence. The fictional scenario ESS_{100} exclusively exhibits *ESR*-periods. As a result, we obtain four signal scenarios that demonstrate different intensities of feed-in management actions or, more specifically, different *ESR*-period occurrences.

We solve the problem once for each signal scenario under objective *ES* and varied control parameter n in the range [1,50]. Figure 3.12 depicts the relative share of energy consumption in *ESR*-periods depending on the value of control parameter n for each of the scenarios. We observe that even low control parameters n achieve at least 93 % energy consumption in *ESR*-period in the scarce scenario ESS_{75} and a somewhat higher consumption rate in the scenario ESS_{80}. In these scenarios 100 % *ESR*-period consumption is only achieved for considerably higher values of n, which would mean that the planning can look sufficiently far ahead to schedule jobs and charging operations within upcoming *ESR*-periods. If such *ESR*-periods are abundant, as is the case in the scenario ESS_{100}, the PCP can schedule all operations in such periods and achieve 100 % of energy consumption within them. Nevertheless, already scenario ESS_{85}, which has just slightly more *ESR*-periods compared to the current practical situation, allows the PCP to shift all consumption into *ESR*-periods. The influence of the control parameter decreases, the richer the *ESR*-scenario is.

Objective *ES* and its corresponding shift of production and charging processes to *ESR*-periods offers the opportunity to minimize the loss of sustainable energy. As this energy would be lost without an increase of consumption in *ESR*-periods, a CO_2 saving results from consuming energy in these periods instead of *ESG*-periods. We finally quantify this potential by experiment. We solve the problem once for each signal scenario and each primary objective *TA*, *ES* and *PL* under the moderate control parameter of $n = 25$. For the obtained solutions, we quantify the resulting total CO_2 emissions. We

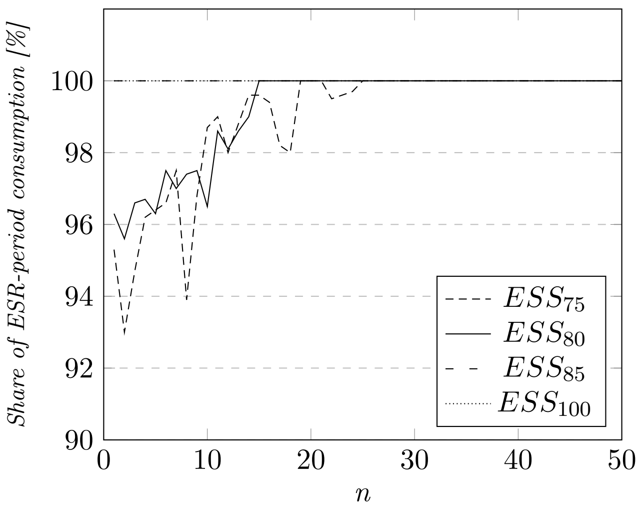

Figure 3.12: Energy consumption depending on external signal scenario.

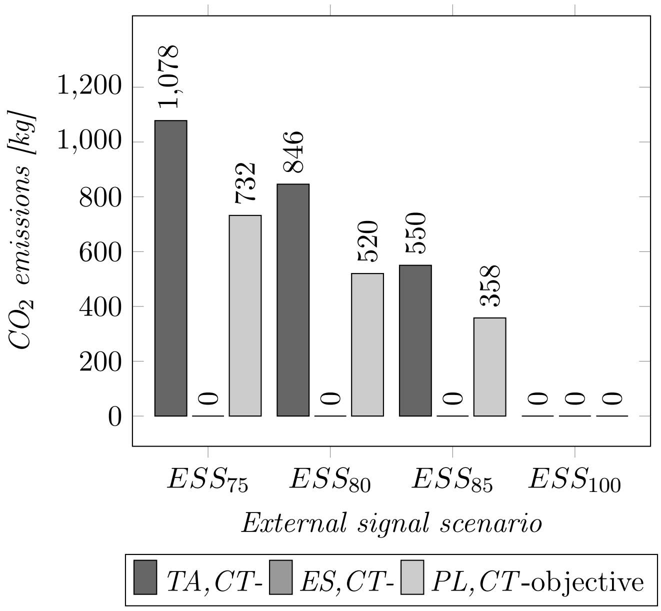

Figure 3.13: CO_2 emissions of solutions under various external signal scenarios.

do this by multiplying the energy consumption in *ESG*-periods by a CO_2 emission factor of 401 g per kWh, which corresponds to the standard energy mix in Germany (Statista 2020). The energy consumption in *ESR*-periods is weighted by 0 g per kWh as this energy is assumed to be lost due to feed-in management if not consumed immediately. Figure 3.13 shows the resulting amounts of CO_2 for each signal scenario and each objective. As expected, the more *ESR*-periods a signal scenario has, the lower are the corresponding CO_2 emissions as there is less production in *ESG*-periods. We also observe that the pure objective *TA* causes by far the highest CO_2 emissions in every scenario whereas objective *ES* shifts production completely into *ESR*-periods in all scenarios. This reflects that objective *ES* achieves the best environmental performance. Still, the alternative objective *PL* provides a trade-off where emissions are reduced by about one third compared to the sole minimization of *TA*.

Eventually, through the various objective functions and the PCP-control mechanism, decision makers gain flexibility to align a company's goals with regard to service quality (*TA*), internal load management (*PL*) and environmental performance (*ES*).

3.5 Conclusion

Peaks in renewable energy generation may require increased local energy consumption to prevent feed-in management actions and to stabilize the power grid. We have presented two optimization models that adapt production scheduling and charging decisions to an external signal that indicates the availability of renewable energy. Using these models, a company can temporarily increase its local energy consumption in times of energy peaks which, in turn, prevents a temporary shut down of wind mills, solar panels etc. The two models consider two heterogeneous types of consumers as to be found in industrial facilities, namely production machines that are driven by job scheduling decisions and support devices that call for charging decisions to manage their inventory. As companies can hardly control these diverse heterogeneous consumers within a single, holistic decision making process, we have presented a production coordination platform that orchestrates the individual decision making processes of these equipment types through a triggering of smart agents. Computational experiments have shown that the PCP produces good solutions under diverse service- and environmentally-oriented optimization goals compared to an integrated optimization model. Anyhow, for each such goal, it was required to consider the minimization of job completion times as a subordinate objective to guarantee high service levels. We also analyzed the impact of a PCP-control parameter, which can be interpreted as the availability of information that the platform requires for making its decisions. Our experiments have shown that the PCP can deal with imperfect information but the more information it receives the better the service level of the obtained solutions is. We also demonstrated that further subordinate objectives can additionally improve the solutions. In view of the environmentally-oriented optimization goals, the presented PCP is capable to make an essential contribution to CO_2 reduction. The planning approach proposed in this paper can assist companies in coordinating their heterogeneous equipment types and in aligning production and charging processes under a range of relevant objectives. Finally, as the presented PCP follows a modular design, it can also handle larger numbers of machines and more diverse support devices as those considered in our experiments, as long as the individual decisions of each such type of equipment are captured in a suitable decision support model that is executed through a corresponding smart agent.

Regarding future research, it may be of interest to include non-linear charging patterns that are often observed for various types of support devices in practice. It could also be interesting to examine the role of uncertainty in the forecasted external signal. Finally, political instruments that incentivize companies to adapt their operations and energy consumption to the availability of renewable energy are also considered relevant for future research.

Acknowledgments

The authors would like to thank the Gesellschaft für Energie und Klimaschutz Schleswig-Holstein GmbH (EKSH) for promoting this project in form of a PhD scholarship.

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Chapter 4

Decentral decision-making for energy-aware charging of intralogistics equipment

Publication status Published in 2023: *Logistics Research* 16: 4. https://doi.org/10.23773/2023_4

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Abstract Industrial manufacturing is based on a variety of energy sources, e.g. electricity, oil, and gas. Electricity appears to be particularly relevant to operate most types of industrial production equipment in an environmentally friendly manner. Aside from production machines, intralogistics equipment that performs material handling and supplies processes is a further consumer of electricity in an industrial environment. The integration of electricity-intensive intralogistics equipment has, however, hardly been considered in the research on energy-aware production management. With this paper, we present an optimization model that synchronizes intralogistics charging decisions with a production schedule and the availability of renewable electricity in a power grid. Following the *Industrie 4.0*-paradigm, we use decentralized decision-making within an agent-based platform that coordinates different types of production and intralogistics equipment. We integrate a forecast signal for the availability of renewable energy into this platform to support an environmentally oriented decision process. In a simulation study that is based on real-world data, we analyze the role of intralogistics handling processes and charging operations with respect to a company's job shop environment and electricity consumption profile. In this simulation, we compare static charging policies in contrast to the proposed optimization model and decentral decision-making under various demand scenarios. The presented approach is shown to be capable of increasing local electricity consumption in times of peak generation of renewable energy, which contributes to CO_2 reductions in industrial manufacturing.

Keywords Intralogistics charging decision, demand response, renewable energy, CO_2 emission, decentral decision making

4.1 Introduction

In 2021, Germany emitted a total of 675 million tons of CO_2 Statista (2023). Industrial manufacturing contributed significantly to this emission and electricity appears to be particularly relevant to operate the majority of production equipment, as the industry sector accounts for a large share of Germany's overall electricity consumption Eurostat (2022b). Increasing electricity generation from renewable energy sources is considered the central approach to reduce CO_2 emissions. At present, however, the potential is not being fully exploited as insufficient grid capacity cannot handle peaks in renewable energy generation, which results in feed-in management and losses of renewable energy generation (Eurostat 2022a). More precisely, a loss of 5,818 GWh of renewable energy by feed-in management actions was caused in Germany in the year 2021 (Bundesnetzagentur 2021). Assuming a CO_2 emission factor of 420 g per kWh, corresponding to the standard electricity mix in Germany in 2021, potential CO_2 savings of approximately 2.44 million tons CO_2 were lost due to this (Umweltbundesamt 2022).

Besides costly and time-intensive expansions of grid infrastructure, energy-aware research, in particular event-driven demand response in the form of adaptable local industrial electricity consumption, offers an opportunity to counteract renewable energy generation losses. While energy-aware research greatly focuses on production planning and specifically machine scheduling, little attention has been put on closely linked and mandatory electricity intensive *intralogistics* supply processes, like, for example, material handling or production factor supply. Aside from machine scheduling, intralogistics can have a considerable impact on a company's overall electricity consumption. Therefore, it seems appropriate to widen the focus of energy-aware research to also account for intralogistics processes in order to exploit further potentials of CO_2 emission reduction.

For this purpose, the paper at hand adopts a decentral decision-making methodology to orchestrate machine scheduling and intralogistics charging decisions taking into account the availability of sustainable energy in the course of time. We introduce an optimization model with the objective of synchronizing charging decisions of intralogistics equipment to the availability of renewable energy. More precisely, the considered company receives a forecast signal that indicates whether feed-in management is necessary for upcoming periods. This forecast corresponds to the so-called Netzampel (AG 2022), which provides information about the availability of excessive renewable energy at a regional level. Excessive renewable energy is indicated by a red color Netzampel in the municipality and, thus, feed-in management is necessary (external signal red, *ESR*). For a local company, this forecast signal indicates that energy-intensive operations could be conducted to consume renewable energy that would otherwise be lost. A green Netzampel forecast (external signal green, *ESG*) indicates, that feed-in management is not needed. Following this approach means that an opportunity is given to synchronize industrial manufacturing processes with renewable energy generation and to contribute to industrial CO_2 emission reduction. We benchmark our intralogistics charging optimization model against well-known static charging policies.

The remainder of this paper is organized as follows. Section 4.2 reviews the relevant energy-aware literature. Section 4.3 puts emphasis on the decentral decision-making process under consideration of the availability of renewable energy. Subsequent computational experiments in Section 4.4 analyze and evaluate the performance of the presented approach. Section 4.5 concludes the paper.

4.2 Literature review

Energy awareness in industrial manufacturing decision-making is addressed in numerous recent publications and several literature reviews, see for example Gahm et al. (2016). Energy awareness in manufacturing environments means incorporating energy price variations or events like special weather conditions to align energy consumption with manufacturing processes. In this line of thought, demand-side management encourages companies to adopt energy consumption to a targeted demand response event. A distinction can be made between prevalent price-driven and rare event-driven demand response approaches (Biel and Glock (2016)). The analysis of publications reveals a focus on price-driven demand response and emphasizes a need for research that accentuates event-driven demand response to which this paper contributes through the conducted investigation.

As an example of price-driven demand response, Busse and Rieck (2022) investigate a flow shop scheduling problem integrating mid-term electricity price forecasts to minimize energy costs under a real-time pricing (RTP) scheme. Lu et al. (2021) propose a RTP prediction approach based on a neural network to minimize electricity costs while satisfying production requirements of a serial production line. Based on manufacturing systems with cyber-physical systems, Yun et al. (2022b) contribute a real-time demand response strategy to reduce electricity costs. In consideration of the large number of energy-aware decision support models, we refer to the following literature reviews for a detailed insight: While Renna and Materi (2021) provide an overview with a special highlight on studies that consider renewable energy source integration in manufacturing systems, Bänsch et al. (2021) study a wide range of relevant energy-aware scheduling publications in depth. The publication by Bänsch et al. (2021) points out that demand response literature predominantly focuses on machine scheduling and only a few publications additionally integrate the effect of manufacturing supply processes, which we discuss hereafter.

From the large body of energy-aware machine scheduling research, Bänsch et al. (2021) report streams of recent developments and identify future research potentials. Apart from on-site generation environments, dynamics, rescheduling, and usage of multiple forms of energy, the authors mention a need for the integration of intralogistics transportation processes. From an integrated environmental viewpoint, it seems reasonable to furthermore account for energy-intensive intralogistics together with production-related job scheduling. Regarding transportation processes, Liu et al. (2019) consider a flexible job shop scheduling problem and integrate crane operations to transport workpieces on the shop floor while minimizing both, the total cost of consumed energy and the schedule makespan. Hemmati Far et al. (2019) emphasize a flexible manufacturing cell setting with industrial robots, where automated guided vehicles (AGVs) are used to transport material between storage and manufacturing areas. The proposed model minimizes overall production and transport cost under time-of-use (TOU) electricity prices to account for the energy consumption of moving AGVs within the manufacturing environment as well as job tardiness. Expanding the focus, Wang (2019) extends the company boundary and integrates finished product distribution in the sense of vehicle routing in combination with single machine scheduling to minimize carbon emissions from the production equipment's energy consumption and the fuel consumption of delivery trucks. Hahn-Woernle and Günthner (2018) investigate the effect of power-load management on the throughput of material-handling systems in automated warehouses and demonstrate that power limits are capable to avoid energy consumption peaks, while slightly reducing the throughput.

Relating to equipment charging decisions, a demand response method for an integrated manufacturing scheduling and material handling charging system is proposed by Yun et al. (2022a). Under a time-of-use electricity tariff, the approach minimizes the electricity costs of production schedules. The authors integrate a price-driven demand response approach and integrate material handling equipment charging decisions. Compared with this, Scholz and Meisel (2022) consider an event-driven demand response setting and propose a platform to coordinate machine scheduling and intralogistics charging decisions. The paper at hand expands the approach of Scholz and Meisel (2022) by putting a special focus on charging decisions of energy-intensive intralogistics equipment, where we align these decisions to machine schedules under various static charge policies and an optimization-driven approach.

4.3 Decentral agent-based intralogistics charging

First, in Subsection 4.3.1, the underlying manufacturing environment is introduced. Then, Subsection 4.3.2 introduces the intralogistics charging decision optimization model. Conclusively, Subsection 4.3.3 presents the algorithm that specifies the considered decentral decision-making and provides explanations for the static charging policy procedures.

4.3.1 Problem description

In what follows, we consider a manufacturing environment that can be divided into two general segments. A schematic framework of this environment is depicted in Figure 4.1. The outer segment includes intralogistics devices (ile) like, for example, equipment for material handling or production factor supply. The inner segment refers to production scheduling where machines (m) have to execute manufacturing jobs. While machines call for job scheduling decisions, intralogistics face charging decisions. The proposed approach can be applied to various kinds of manufacturing environments that involve energy-intensive intralogistics processes like material handling and machine operations such as laser cutting, melting, welding, pressing, or others.

The intralogistics environment, depicted in orange in the figure, consists of k intralogistics equipment depicted as circles. As intralogistics processes, we consider an electrified forklift fleet performing material handling or air compressors providing compressed air as a production factor. Accordingly, we distinguish between intralogistics equipment providing production factors to machines, symbolized by solid arrows, and intralogistics equipment performing material handling between the machines on the shop floor, sym-

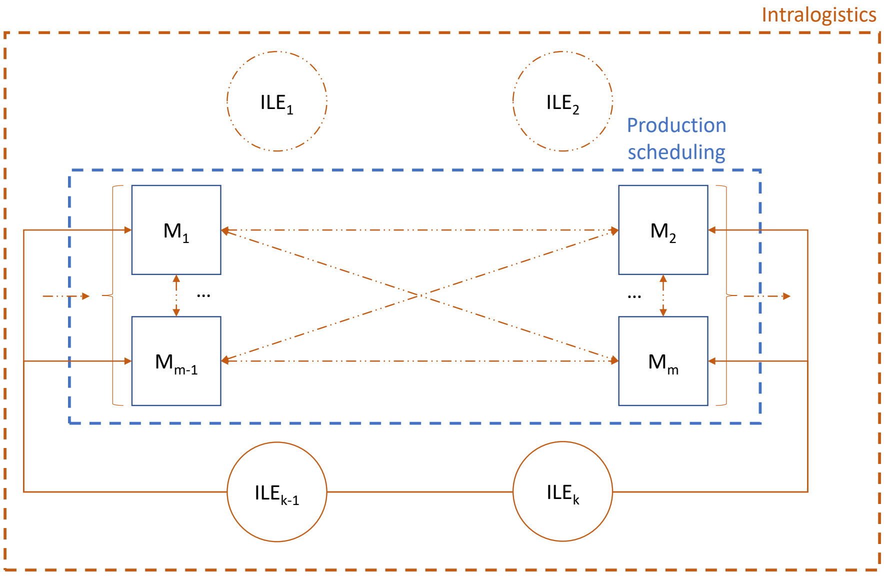

Figure 4.1: Schematic manufacturing environment framework.

bolized by dotted arrows. We put emphasis on the intralogistics charging decisions that need to provide sufficient resources to the production scheduling environment and ensure an adequate inventory (like battery energy level in the case of forklifts or compressed air in the case of compressors) by making charging decisions. A detailed view into the intralogistics environment decision-making is provided in Section 4.3.2.

The production environment, depicted in blue in Figure 4.1, comprises job scheduling decisions for machines. In what follows, we consider the individual decisions within the production scheduling segment as given and the corresponding decision-making process as a *black box*. For the sake of completeness and to make the paper self-contained, we shortly introduce the production scheduling setting. The production scheduling environment consists of n machines, depicted as squares in the figure, that process a set of jobs J. Each job $j \in J$ consists of a set of operations $o \in O_j$ that have to be processed in a specified order, and, thus, job-specific precedence relations exist where each job exhibits an individual machine routing. Each operation o can be processed in one of three different processing modes, $|S|= 3$. Job processing time $p_{o,s}$ is measured in periods and varies for the three processing modes $s \in S$. The electricity consumption of modes is reflected by rates $q_{o,s}$. There is a trade-off between processing time and electricity consumption such that choosing a processing mode with a higher processing speed leads to an electricity consumption increase. Furthermore, jobs exhibit release dates r_j that refer to the earliest period in time at which processing can be started.

The majority of research considers production scheduling and inventory-based charging decisions as independent problems. The literature review in Section 4.2 revealed that recent publications bring these two research streams together and formulate integrated approaches, which seems reasonable as both exert a decisive influence on a company's electricity consumption. In what follows, we, therefore, propose an agent-based decentralized decision-making platform that acts as an interface between the production scheduling and intralogistics decision-making environments. In order to focus on the impact of intralogistics decision-making, we consider the detailed process within the production scheduling segment as a black box and production decisions as given. To get a detailed view of intralogistics decision-making, we propose a mathematical model formulation that constitutes an extension of the model provided by Scholz and Meisel (2022). In order to orchestrate intralogistics processes in coordination with production scheduling decisions, we put emphasis on decentralized decision-making. To this end, the next Section 4.3.2 describes the intralogistics charging decision-making that is triggered through the decentral decision-making procedure. Section 4.3.3 then represents the decentral decision-making procedure, where individual agents hold the intralogistics and production scheduling decision rules.

4.3.2 Optimization model for intralogistics charging decisions

In this section, we consider a single intralogistics equipment (*ile*) that assists machines in their production operations. The intralogistics inventory charging needs to be aligned with the machines' production operations to avoid disruptions of the production processes. For this purpose, we present an optimization model that covers intralogistics charging decisions with respect to demands that result from machine scheduling decisions. We denote by T the set of upcoming periods for which charging decisions have to be made. This set can be derived from the periods the machines have scheduled their jobs so far. The considered intralogistics equipment exhibits an initial inventory inv_0 and a maximum inventory capacity inv_{max} where recharging can take place in different charging modes S. The availability of different modes allows to trade-off the charge speed versus the electricity that is consumed per period of charging. Accordingly, they differ in power consumption q_s and charge rate c_s. The charge rate expresses the electricity charged to the battery for a forklift whereas it expresses the added amount of compressed air for an air compressor or similar inventories for other types of equipment. The jobs scheduled on the machines constitute the intralogistics equipment period-based demands de_t for periods $t \in T$ that consume the intralogistics equipment's inventory. From the job scheduling decisions of all machines being active in a period, we can derive a total demand de_t faced by the considered intralogistics equipment in period t. Whether or not the intralogistics equipment faces such a demand in period t is indicated by the binary parameter ϕ_t, which is equal to 1 if $de_t > 0$ and 0 otherwise. According to technical realities, especially in view of forklift batteries, a certain self-discharge amount sdc per period is taken into account. Furthermore, intralogistics equipment can be distinguished by whether or not they are capable of simultaneous charging and inventory consumption (binary parameter $scc = 1$) or not ($scc = 0$). The charging decision for the intralogistics equipment is then modeled through the binary decision variable $z_{s,t}$, which is equal to 1 if the equipment charges in mode $s \in S$ in period $t \in T$. The dependent continuous variable inv_t keeps track of the resulting inventory. Table 4.1 summarizes the notation for this model. The optimization model for the charging decisions of the intralogistics equipment is then as follows.

Table 4.1: Notation for intralogistics charging decisions.

Sets	
T	Set of periods
S	Set of charging modes
Parameters	
inv_0	Initial inventory [l, Wh, or similar dimensions]
inv_{max}	Maximum inventory capacity [l, Wh, or similar dimensions]
de_t	Demand faced in period $t \in T$ [l, Wh, or similar dimensions]
ϕ_t	Equal to 1 if there is demand in period t (i.e. $de_t > 0$), 0 otherwise
q_s	Power consumed per period of charging in mode s [kW per period]
re_t	Dichotomous parameter, with $re_t = -1$ if forecast indicates feed-in management (ESR) in period t, otherwise $re_t = 1$ (ESG)
c_s	Inventory charged per period in charging mode s [l, Wh, or similar dimensions]
sdc	Self discharge per period [%]
scc	Equal to 1 if the equipment is capable to charge and consume inventory at the same time, 0 otherwise
Decision variables	
$z_{s,t}$	Binary variable, 1 if equipment charges in mode s in period t, 0 otherwise
inv_t	Dependent continuous variable stating the equipment's inventory at the end of period t [l, Wh, or similar dimensions]

$$\min \rightarrow \sum_{s \in S} \sum_{t \in T} z_{s,t} \cdot q_s \cdot re_t \tag{4.1}$$

$$\sum_{s \in S} z_{s,t} \leq 1 \qquad t \in T \tag{4.2}$$

$$inv_t = inv_{t-1} - de_t + \sum_{s \in S} z_{s,t} \cdot c_s - \left(1 - \sum_{s \in S} z_{s,t}\right) \cdot sdc \qquad t \in T \tag{4.3}$$

$$\sum_{s \in S} z_{s,t} + \phi_t \leq 1 + scc \qquad t \in T \tag{4.4}$$

$$0 \leq inv_t \leq inv_{max} \qquad t \in T \tag{4.5}$$

$$z_{s,t} \in \{0, 1\} \qquad s \in S, t \in T \tag{4.6}$$

The objective function (4.1) represents the intralogistics inventory charging synchronization with the dichotomous renewable energy forecast parameter re_t, with $re_t = -1$ if the forecast indicates feed-in management (ESR) in period t and $re_t = 1$ if no feed-in management is necessary (ESG). Through this, the objective maximizes the electricity consumption to charge intralogistics inventory in times of excessive renewable energy generation (feed-in management, ESR) and minimizes electricity consumption in periods without feed-in management (ESG). Feasibility of the charging decisions is ensured by Constraints (4.2) to (4.6). Constraints (4.2) assure that at most one charge mode can be chosen for a period. Constraints (4.3) compute the inventory inv_t at the end of period t taking into account the inventoryinv_{t-1} at the end of the previous period, the demand de_t in the current period, and the new charge $z_{s,t} \cdot c_s$. Furthermore, according to the last term in these constraints, the inventory is reduced from the self-discharge sdc in periods where the equipment is not charging. Constraints (4.4) satisfy that an intralogistics equipment that is capable of simultaneous charging and inventory consumption (resp. demand fulfillment) ($scc = 1$), can do both in a single period whereas other equipment either charges or consumes inventory in a period ($scc = 0$). Constraints (4.5) ensure the non-negativity of intralogistics inventory and respects the maximum capacity. Constraints (4.6) guarantee the binary character of variables $z_{s,t}$.

4.3.3 Decentral decision-making procedure

The intralogistics charging optimization model introduced in Section 4.3.2 is embedded in an agent-based platform to coordinate the decentral decision-making of production machines and intralogistics equipment. The decision-making is then performed on a server infrastructure by embedded *smart agents* that hold the individual decision rules for the production scheduling and intralogistics environment. Based on the definition of an intelligent agent of Wooldridge (2002), a smart agent is understood as a computer program that executes autonomously triggered rules and processes. For the subsequent experiments, we simulate the behavior of such a platform through the procedure that is sketched in Algorithm 1. In this algorithm, the multi-agent system is implemented as a priority queue of requests placed by the equipment. Requests represent an equipment's production inquiry, e.g. in order to schedule jobs or to recharge intralogistics inventory. These requests incrementally build a production and charging schedule in a rolling horizon manner. While a real-time approach requires continuous data input, constant data processing, and continuous data output with low latency, the presented approach behaves like a near real-time approach, as data handling is linked to the manufacturing equipment request times. This coupling reduces the amount of necessary data handling compared to a real-time approach and still delivers real-time alike solutions.

Contrasting the introduced intralogistics charging decision optimization model of Section 4.3.2, static charging policies are a common instrument for making charging decisions in practice. In the following, we take into consideration four well-known and established inventory review policies. In general, we can distinguish these static policies into periodic charging procedures (t, q-policy, t, S-policy) and continuous procedures (s, q-policy, s, S-policy). Regarding periodic charging procedures, charging takes place at given and fix time intervals t where either a fixed amount q is charged or it is charged until the order-up-to level S is reached. On the contrary, continuous charging procedures initiate charging when the state of charge (inventory) falls below a defined threshold, the order point s. Then, either a fixed amount q is charged or charging takes place until the order-up-to level S is reached. Consequently, the proposed decentral decision-making platform is capable to account for four static charging policies and to apply the optimization model to charge intralogistics equipment.

In more detail, lines 1 to 7 of Algorithm 1 initiate essential sets, lists, the priority queue, and initial request periods. The processing of the priority queue starts at line 8. It first identifies the next request according to the period at which requests occur, see line 9. The agent then receives the current load profile lp_t and feed-in management forecast re_t

Algorithm 1 Decentral decision-making procedure.

$E \leftarrow M \cup ILE$ ▷ *set of equipment (production machines and intralogistics equipment)*
$U = [\ ]$ ▷ *list of unprocessed jobs*
$P = [\ ]$ ▷ *list of processed jobs*
$q \leftarrow priority\ queue()$ ▷ *initialize priority queue*
for $e \in E$ **do**
  $e.request \leftarrow initial\ request\ period$ ▷ *assign initial request period*
  $q.put(e)$ ▷ *place request in priority queue*
while $q \neq \emptyset$ **do**
  $e \leftarrow q.get()$ ▷ *select next trigger event from priority queue*
  smart agent retrieves relevant information lp_t, re_t
  if e refers to a *production machine* **then** ▷ *request equipment type 'machine'*
    compare required capacity with intralogistics equipment inventory
    if insufficient intralogistics equipment inventory **then**
      $e.request \leftarrow next\ request\ period$ ▷ *postpone machine request*
      $ile.request \leftarrow next\ request\ period$ ▷ *define next intralogistics equipment request*
      $q.put(ile)$ ▷ *insert ile into priority queue*
    else
      call machine scheduling model as black box ▷ *see* Scholz and Meisel (2022)
      $e.request \leftarrow next\ request\ period$ ▷ *next request when machine runs idle*
      transmit production decisions to machine
      update de_t ▷ *derive intralogistics equipment demand from production decision*
      for $ile \in ILE$ **do**
        if $charge\ policy = s, q$ **OR if** $charge\ policy = s, S$ **then**
          if $ile.inventory \leq s$ **then**
            $ile.request \leftarrow next\ request\ period$ ▷ *define next request*
            $q.put(ile)$ ▷ *insert intralogistics equipment into priority queue*
      for $j \in U$ **do**
        if job j's final operation was executed **then**
          $U.remove(j)$ ▷ *remove job from list of unprocessed jobs*
          $P.append(j)$ ▷ *add job to list of processed jobs*
  if e refers to an *intralogistics equipment* **then** ▷ *request equipment type 'intralogistics'*
    smart agent retrieves relevant information de_t
    if $charge\ policy = t, q$ **OR if** $charge\ policy = s, q$ **then**
      if $e.inventory + q \leq e.inv_{max}$ **then**
        $e.inventory \leftarrow e.inventory + q$ ▷ *charge with quantity q*
    if $charge\ policy = t, S$ **OR if** $charge\ policy = s, S$ **then**
      $\Delta = S - e.inventory$
      $e.inventory \leftarrow e.inventory + \Delta$ ▷ *charge with quantity Δ*
    if $charge\ policy = t, q$ **OR if** $charge\ policy = t, S$ **then**
      $e.request \leftarrow next\ request\ period$ ▷ *next request in t periods*
    if $charge\ policy = optimization\ model$ **then**
      solve model (4.1)–(4.6) ▷ *solve intralogistics optimization model*
      $e.inventory \leftarrow e.inventory + z_{s,t} \cdot c_s$ ▷ *charge with quantity $z_{s,t} \cdot c_s$*
      $e.request \leftarrow next\ request\ period$ ▷ *next request when intralogistics equipment runs idle*
  update lp_t
  $q.put(e)$ ▷ *put next request in priority queue*

in the considered period t (line 10). The current load profile lp_t reflects the company's already fixed electricity demand in period t that results from those operations that were planned in earlier decision-making processes. The feed-in management forecast re_t indicates upcoming excessive renewable energy generation. For a better understanding of the parameters lp_t and re_t a brief example is as follows: With $lp_1 = 1{,}500$ and $re_1 = -1$, the parameters represent an electricity demand of 1,500 kWh and the dichotomous parameter re_t indicates feed-in management (*ESR*) in period $t = 1$. Afterwards, it is checked whether the trigger event e belongs to a machine or intralogistics equipment.

In case a machine requests to schedule new production jobs (line 11), intralogistics inventories need to meet the upcoming machine demands de_t. Otherwise, the production scheduling request is postponed to meanwhile recharge the intralogistics equipment, see lines 13 - 16. In case of sufficient intralogistics inventory, the machine is capable to proceed with production scheduling, see lines 18 - 20. The newly scheduled jobs constitute a new demand for intralogistics inventory, which is reflected in the update of de_t in line 21. Referring to the case where charge policies (s, q) or (s, S) are implemented for intralogistics charging, a constant inventory verification is essential to ensure that the inventory lays above the order point s. If the inventory falls below the defined order point, lines 22 - 26 define the next intralogistics request to initiate an immediate charging process. Lines 27 - 30 complete the *production machine* request procedure. Through this, when a job's final operation is executed, the job is moved from the list of unprocessed jobs to the list of processed jobs.

In case the triggered event refers to an intralogistics equipment's request for charging (line 31), the agent receives the relevant demand information de_t (line 32). In case of a charge policy with constant charge rate q $(t, q;\ s, q)$, the intralogistics inventory is charged with quantity q, in case the maximum inventory capacity inv_{max} allows for this (lines 33 - 35). Similarly, when a charge policy with a given order-up-to level S $(t, S;$ $s, S)$ is used by the company, the intralogistics inventory is charged with a quantity Δ that brings the inventory up to level S, see lines 36 - 38. In case of a periodic charging procedure $(t, q;\ t, S)$, the next request will be triggered at the time of the current period plus charge interval t, see lines 39 - 40. If the charging decisions are made through the optimization model (4.1)–(4.6), line 42 solves the model, line 43 updates the inventory according to the model's charging decisions, and line 44 schedules the next event for the period in time when the equipment runs idle for the next time. Having handled the request of the current event e, the load profile lp_t is updated to capture the electricity demand of the taken decisions (line 45). Finally, the follow-up request is added to the priority queue (line 46), for example, to trigger an intralogistics smart agent again as soon as a charging decision is necessary.

4.4 Computational experiments

In the following, Subsection 4.4.1 introduces the computational study setup, while Subsection 4.4.2 describes the charge policy interval parameterization. Based on that, Subsection 4.4.3 contrasts the static charging policies to the optimization model approach. Subsection 4.4.4 concludes the computational experiments by considering the impact of different intralogistics demand lengths.

4.4.1 Computational study setup

Our computational study consists of several experiments that parameterize the static charge policies, compare them to the optimization-driven charging decision-making, and analyze the performance of the approach with respect to variations in intralogistics demand.

The experiments are inspired by a real-world manufacturing company in the metalworking industry from the federal state of Schleswig-Holstein, Germany. The company's manufacturing system consists of a job shop production environment with five machines that operate in batch production. Job processing times are derived from this environment. As the paper at hand considers the production scheduling environment as a *black box*, we do not describe its structure in further detail. The intralogistics devices of the company assist the machines in their production operations. The devices comprise two electric forklifts for material transportation between the machines and one air compressor providing compressed air as a production factor to the machines. Relevant in this context is that the intralogistics equipment has to fulfill the demands that arise from the production scheduling decisions. Table 4.2 shows relevant data of these intralogistics devices.

The inventories of the compressor are measured in liters (l) of compressed air while the inventory of the electric forklifts is measured in Watt-hours (Wh). The general parameters such as the maximum inventory inv_{max} of the compressor and the forklifts are taken from the considered company and from the industrial standardization norm *DIN EN 16796*. All intralogistics equipment exhibits three charging modes $|S|$=3 with different charge rates c_s and electricity consumption rates q_s for mode $s \in S$. According to technical realities, the battery of a forklift charges at a rate c_s of approximately 64 % of the corresponding electricity consumption rate q_s. Besides that, the forklift battery's

Table 4.2: Intralogistics data.

Input data	Compressor	Forklift
Maximum inventory inv_{max}	10,000 [l]	36,000 [Wh]
Charge rate per period c_s	769/588/476 [l]	969/923/877 [Wh]
Charging electricity consumption q_s	45,040/41,029/36,929 [W]	6,048/5,760/5,472 [W]
Self discharge amount sdc	0.0 [%]	0.2 [%]
Simultaneous charging/consumption scc	1	0
Initial inventory inv_0	10,000 [l]	36,000 [Wh]
Order point s	2,000 [l]	7,200 [Wh]
Order-up-to level S	8,000 [l]	28,800 [Wh]
Intralogistics demand de_t	500-2,000 [l]	1,400 – 2,925 [Wh]

self-discharge sdc is assumed to be 0.2 % per period whereas the compressor does not face such a discharging ($sdc = 0.0$ %). Furthermore, the air compressor can charge and fulfill production demand simultaneously ($scc = 1$), whereas the forklift can either charge or serve demands in a period ($scc = 0$).

We assume that the initial inventory inv_0 of both types of equipment is identical to the maximum inventory. For the static charge policies, we consider an order point s that corresponds to 20 % of the maximum intralogistics inventory and an order-up-to level S equaling 80 % of the maximum inventory. Individual demand rates de_t of the forklifts and the air compressor vary in the ranges mentioned in Table 4.2 and correspond to the underlying real-world production data. Even though the conducted simulation study is following the outlined manufacturing environment from practice, the proposed model formulation is not limited to these consumers and is applicable to a wide range of inventory-based equipment types.

When conducting the computational experiments, we consider a rolling time horizon of 64 periods and an overall simulation time of 640 periods. A single period corresponds to 15 minutes, according to which the planning time horizon covers two days and the total simulated time of operations equals four weeks with one eight-hour shift per day. The forecast of the availability of excessive renewable energy is derived from Schleswig-Holstein's feed-in management actions in 2021. According to this data, approximately 66 % of the periods face feed-in management actions. All data for the computational experiments are available at the repository [https://www.scm.bwl.uni-kiel.de/de/forschung/research-data]. All computations are conducted on an Intel Core i7 with a 3.6 GHz CPU and 32 GB memory. For solving the optimization model, we use the MIP solver CPLEX

12.9.0. The corresponding computation time per instance of the model is approximately 30 seconds, which is considered sufficiently small and, therefore, not further analyzed in the following. The decentral decision-making environment is implemented in Python 3.7 using the libraries *queue, pandas, numpy*, and *doopl.factory*.

4.4.2 Charge policy interval parameterization

In what follows, we will emphasize the mentioned periodic charging procedures introduced in Section 4.3.3 with a special focus on parameterizing the charge interval t. The order point s, an order-up-to level S, and charge amount q are important parameters as well but are assumed to be given due to (technical) restrictions of the intralogistics equipment. In contrast, the charge interval t is clearly within the company's decision-making authority and exerts a decisive influence on the production scheduling segment, as the machines are reliant on sufficient intralogistics inventory to maintain production. Figures 4.2 and 4.3 demonstrate the charge interval influence. They illustrate the production scheduling job processing rate (right ordinate), which is the percentage of jobs that can be processed within the simulated time horizon, and the intralogistics electricity consumption (left ordinate) for varied values of the charge interval t.

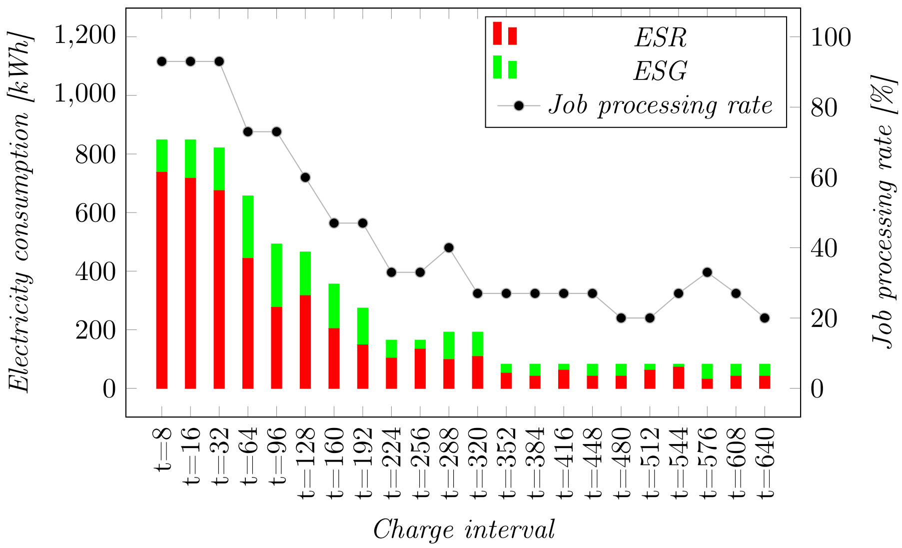

Figure 4.2: (t, q)-policy charge interval parameterization.

In order to define an appropriate charge interval t for the charge policies (t, q) and (t, S), Figures 4.2 and 4.3 represent 22 different charge intervals within the range of 8 to 640 periods. It can be clearly seen that an increasing charge interval t leads to a

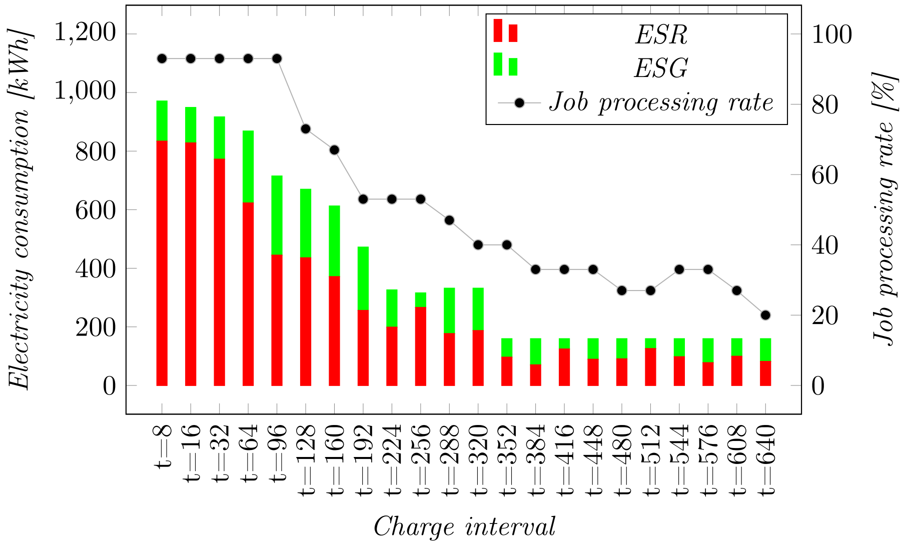

Figure 4.3: (t, S)-policy charge interval parameterization.

decreasing job processing rate and a decreasing intralogistics electricity consumption. We observe that small-scale charge intervals of up to $t = 32$ for the (t, q)-policy and up to $t = 96$ for the (t, S)-policy achieve the maximum possible job processing rate of 93 %. This rate cannot be exceeded in the considered setting as jobs being released shortly before the end of the simulation time cannot be completed (end-of-horizon effect). In contrast, increasing charge intervals t lead to a decreasing job processing rate due to insufficient inventory of the intralogistics equipment. Regarding the extreme case where the charge interval is equal to the simulation time of 640 periods and, hence, only a single charging takes place during the simulation, the job processing rates drop to as little as 20 %.

The total electricity consumption (sum of ESR and ESG) for the charge interval $t = 8$ constitutes the maximum consumption rate. For higher values of t, the total electricity consumption decreases, as increasing time spans between two charge processes result in an overall reduction of the number of charge operations. Thereby, charge intervals within the range of $t = 8$ to $t = 32$ achieve at least 82 % of charging within *ESR* periods. The total electricity consumption is identical for the charge intervals within the range of $t = 352$ up to $t = 640$, which is due to the fact that only a single charge takes place in all these settings. Merely the allocation to periods with necessary feed-in management (*ESR*-periods) and to periods without feed-in management (*ESG*-periods) changes slightly. Differences in the job processing rate for the charge interval range $t = 352$ to $t = 640$ and the slight increase for $t = 288$ can be traced back to variations in the jobs that are selected by the machines due to postponements that are required when charging the intralogistics devices.

Based on these results, the charge interval is set to $t = 32$ for the subsequent computational experiments, which ensures sufficient intralogistics inventory to obtain the maximum possible machine job processing rate when applying a static charging policy.

4.4.3 Static intralogistics charging policy compared to charging optimization model

In this section, we will emphasize the comparison of the introduced charging policies from Section 4.4.2 with the intralogistics charging decision optimization model from Section 4.3.2.

Figure 4.4 contrasts the intralogistics charging electricity consumption and job processing rate for each of the four static charge policies and the optimization model. All charging approaches allow for a machine job processing rate of 93 %, which means that the production scheduling segment is capable to process an identical job amount, regardless of the chosen charging policy. It becomes apparent that all static charging policies additionally reveal lower total electricity consumption compared to the optimization model. Consequently, only the optimization anticipates excessive renewable electricity generation and gives the company's decision maker the opportunity to reduce the loss of renewable electricity generation by fully charging intralogistics devices in *ESR*-periods. From comparing the optimization model's charging decisions to the most electricity-intensive static charging (t, S)-policy, it is possible to make use of additional 326 kWh during *ESR*-periods, which would otherwise be lost due to feed-in management.

In more detail, the (s, q)-policy comes along with a minimum total electricity consumption of approximately 711 kWh. This is followed by the (s, S)- and (t, q)-policies, which show a total intralogistics charging consumption of 731 kWh and 821 kWh, respectively. Only the (t, S)-policy reveals a significantly higher total electricity consumption of about 917 kWh. This difference can be traced back to the periodic intralogistics charging up to the order-up-to level S, when applying a (t, S)-policy. The (t, q)-policy for instance also recharges periodically but charges a constant amount q, which corresponds to 50 % of the intralogistics maximum inventory and is only applied when the upper inventory limit is not exceeded by this. Similar statements hold for the remaining policies. Even though the (s, q)- and (s, S)-policy both initiate intralogistics charging when the inventory falls below the order point s, they marginally differ in the total electricity consumption. The slightly higher electricity consumption of the (s, S)-policy compared

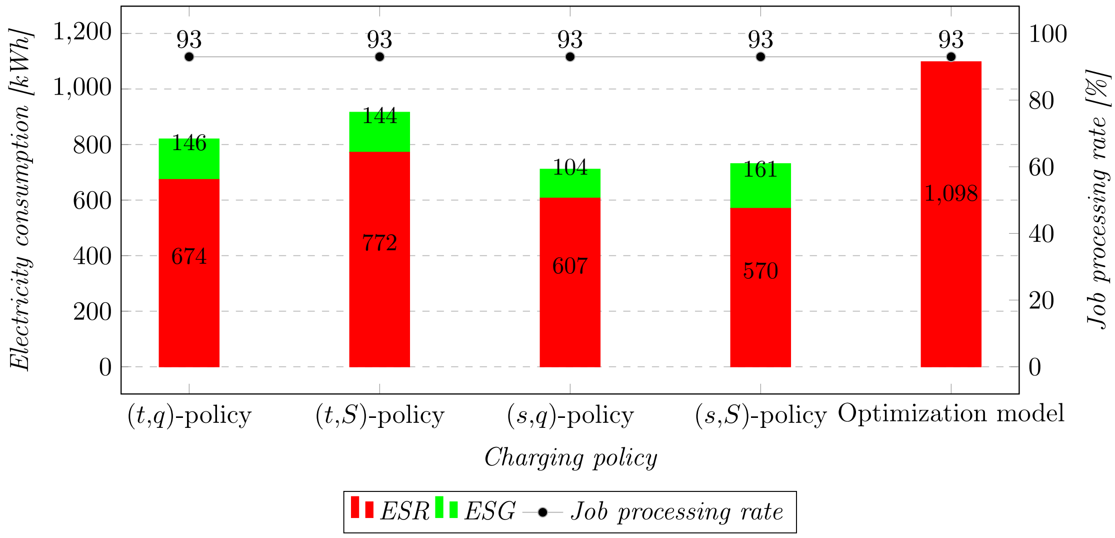

Figure 4.4: Comparison of static charge policies and optimization-driven charging.

to the (s, q)-policy is due to the fact that the order-up-to level S corresponds to 80 % of the intralogistics maximum inventory whereas the charge amount q equals 50 % of the intralogistics maximum inventory.

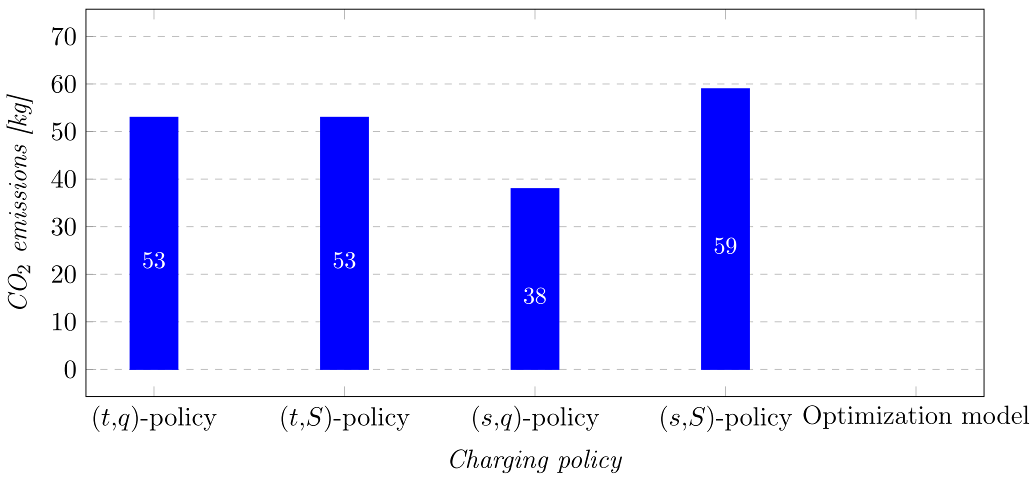

Figure 4.5: Charging policy specific CO_2 emissions.

It should be noted that all static charging policies involve electricity consumption in periods with feed-in management (*ESR*-periods) and without feed-in management (*ESG*-periods) and only the optimization model entirely shifts intralogistics charging decisions solely to feed-in management periods (*ESR*-periods). The (s, S)-policy causes the maximum electricity consumption in *ESG*-periods with 160.88 kWh, followed by the

(t, q)-policy with 146.13 kWh. While the (t, S)-policy induces 144.33 kWh the (s, q)-policy exhibits a minimum of 103.84 kWh electricity consumption in *ESG*-periods. For the obtained solutions in Figure 4.4, we quantify the resulting total CO_2 emissions (see Figure 4.5). We do this by multiplying the electricity consumption in *ESG*-periods by a CO_2 emission factor of 366 g per kWh, which corresponds to the standard electricity mix in Germany in 2020 (Umweltbundesamt 2022). The electricity consumption in *ESR*-periods correlates with 0 g per kWh as this electricity originates from excessive renewable electricity generation and would be lost due to feed-in management if not consumed instantly. Consequently, a charging policy with low *ESG*-period electricity consumption comes along with low CO_2 emissions. In light of this, the (s, q)-policy comes along with the lowest CO_2 emissions of 38 kg among the static charging policies. The (t, q)-and (t, S)-policy exhibit almost identical CO_2 emissions of around 53 kg, whereas the (s, S)-policy causes the highest CO_2 emissions of all static charging policies with around 59 kg. Contrasting the static charging policies, the optimization model completely avoids CO_2 emissions. The CO_2 quantification reveals that applying the proposed intralogistics charging optimization model instead of a static charging policy opens up an opportunity for substantial CO_2 emission reduction in the simulated time horizon. In addition to the mentioned CO_2 emission reduction, a potential cost saving arises from trading emission allowances.

4.4.4 Variation of intralogistics demands

While the computations in the previous section compared the five different charging options with one another, we will subsequently examine the impact of different intralogistics demand lengths. By varying the length over which parameter de_t is applied, we simulate changes in the demand for the intralogistics fulfillment. These changes in the intralogistics demand can either result from changes in machine processing or variations in the intralogistics demand fulfillment. In any case, different demand lengths exert influence with regard to the intralogistics property of simultaneous charging and consumption (*scc*). A minimal example could involve $de_3 = de_4 = de_5 = 100$, an intralogistics equipment with no simultaneous charging and consumption ($scc = 0$) being capable to recharge inventory at the earliest in $t = 6$ and constituting a potential bottleneck for machine processing. On the contrary, an intralogistics equipment that is capable of charging and consuming simultaneously ($scc = 1$) can recharge in periods 3 to 5 while fulfilling the demand $de_3 = de_4 = de_5 = 100$, which would not result in a production bottleneck. As a consequence, the variation of intralogistics demand lengths might demonstrate potential adverse interactions between the intralogistics environment with the production environment.

Tables 4.3 to 4.8 summarize the impact of demand length variations on a set of key performance indicators (KPIs). The tables represent the charging policy impact on the KPIs that are reported in the table rows and demonstrate a row-based KPI data relation in the sense of a heat map. Here, the dark green color depicts the best possible KPI value among all charging policies and demand length settings, whereas the dark red color represents the weakest performance. Note that high ESR electricity consumption rates but low ESG rates are desirable in order to counteract excessive renewable electricity generation. Apart from the already introduced performance measures *ESR*, *ESG* and *job processing rate*, we additionally account for four other KPIs. We here introduce *relative ESR usage* as the percentage of intralogistics charging decisions during *ESR* periods. Three further KPIs measure insufficiencies of intralogistics inventory and the consecutive effects for machine scheduling. The *machine postponement* KPI refers to lines 12 to 16 of Algorithm 1 and reports how often machine scheduling needs to be postponed to a later point in time due to insufficient intralogistics inventory. In this line of thought, the *compressor delay* and *forklift delay* specify, which insufficient intralogistics inventory caused the machine postponement. The reported KPIs exert practical relevance with regard to production and energy-related goals. The job processing rate in combination with the underlying machine postponement, compressor delay as well as forklift delay is of particular business relevance, whereas ESR, ESG, and the relative ESR usage focus on the company's energy profile. As an upper bound, for the setting with five machines and a simulation time of 640 periods a maximum possible *machine postponement* of $5 \cdot 640 =$ 3,200 could be observed in case that each machine request is postponed in each period. We further distinguish settings where the forklift that has the highest inventory is selected for fulfilling a demand (Tables 4.3-4.5) and where one forklift is used consistently until it has insufficient capacity at which point the demands are assigned to the second forklift while the first one is recharging, and so on (Tables 4.6-4.8).

Table 4.3 reports the KPIs for the default demand length of one period, which corresponds to the results depicted in Figure 4.4 in Section 4.4.3. The table reveals that all charging policies allow for a job processing rate of 93 % whereby only the (s, q)- and (s, S)-policy come along with a bit of machine postponement. This postponement is due to insufficient compressor inventory but does not reduce the achievable job processing rate. The forklift inventory is sufficient in this demand length setting for all charging policies. Using these results as a reference for comparison, Table 4.4 represents the results under a demand length of two periods. With respect to the job processing rate,

Table 4.3: Charging policy comparison with one period demand length and forklift selection by highest inventory.

KPI	t,q-policy	t,S-policy	s,q-policy	s,S-policy	Optimization model
ESR [kWh]	674.48	772.37	607.35	570.46	1098.44
ESG [kWh]	146.13	144.33	103.84	160.88	0.00
Relative ESR usage [%]	82	84	85	78	100
Job processing rate [%]	93	93	93	93	93
Machine postponement	0	0	3	4	0
Compressor delay	0	0	3	4	0
Forklift delay	0	0	0	0	0

Table 4.4: Charging policy comparison with two periods demand length and forklift selection by highest inventory.

KPI	t,q-policy	t,S-policy	s,q-policy	s,S-policy	Optimization model
ESR [kWh]	1139.31	1438.94	696.43	697.87	1812.70
ESG [kWh]	255.72	313.68	124.17	175.28	0.00
Relative ESR usage [%]	82	82	85	80	100
Job processing rate [%]	73	93	47	47	93
Machine postponement	183	24	584	463	0
Compressor delay	183	24	581	368	0
Forklift delay	0	0	3	95	0

Table 4.5: Charging policy comparison with three periods demand length and forklift selection by highest inventory.

KPI	t,q-policy	t,S-policy	s,q-policy	s,S-policy	Optimization model
ESR [kWh]	1227.86	1528.02	387.98	867.21	2234.09
ESG [kWh]	413.37	424.71	49.67	162.14	0.00
Relative ESR usage [%]	75	78	89	84	100
Job processing rate [%]	53	60	20	33	73
Machine postponement	421	221	1556	1263	152
Compressor delay	421	202	1188	723	152
Forklift delay	0	19	368	540	0

only the (t, S)-policy and the optimization model are capable of realizing the highest possible performance whereas all other static charging policies lead to a clear drop in performance. Especially the (s, q)-policy and the (s, S)-policy show very high machine postponement values such that, eventually, a large share of the jobs cannot be processed at all. The KPI compressor delay reveals that insufficient compressor inventory is the predominant reason for this. It should be noted that the (s, S)-policy additionally exhibits a comparably high forklift delay. When comparing the optimization model results for the one and two period demand lengths, we observe a higher overall electricity consumption with increasing demand length but the model still satisfies all of this through renewable energy that would otherwise be lost (see row *ESR*). Under a demand length of three periods, Table 4.5 reveals that the job processing rate further decreases, now for all charging policies. Still, the optimization model reveals the lowest machine postponement and a consistent usage of *ESR*-electricity.

In contrast to the results in Tables 4.3 to 4.5 where material handling is executed by the forklift with the highest current inventory level, Tables 4.6 to 4.8 show the results for a setting where material handling is executed by only one forklift before this one has insufficient capacity and is replaced by the second forklift while it charges. We observe that the general findings do not change from this alternative forklift deployment strategy. Except for marginal differences in *ESR*- and *ESG*-period electricity consumption, the consistent forklift selection provides similar results as a selection of forklifts according to the highest inventory for demands of one period length, see Tables 4.3 and 4.6. Table 4.7 shows that consistent forklift selection is capable of entirely avoiding insufficient forklift inventory (*forklift delay* $= 0$ for all charging policies) without any change in the job processing rate compared to Table 4.4. It should be noted that the forklift selection mechanism may increase the compressor delay as changes in the machine scheduling decisions due to better forklift inventory utilization are accompanied by further compressor demands. This is observed here for charging policy (s, q) and may be at the expense of the battery's state of health.

Comparing the results for a demand length of three periods in Tables 4.5 and 4.8, we observe that the consistent forklift selection completely eliminates forklift delays under the (s, q)-policy and drastically reduces them under the (s, S)-policy. However, only the (s, S)-policy benefits from this in terms of a higher job processing rate, which increase from 33 % to 40 %. Even though the forklift delays under the (s, q)-policy can be completely eliminated, the remaining compressor delays prevent a higher job processing rate. This is due to the fact that both compressor and forklift inventory are insufficient for a multitude of machine requests and the reduction of a single bottleneck cannot increase

Table 4.6: Charging policy comparison with one period demand length and consistent forklift selection.

KPI	t,q-policy	t,S-policy	s,q-policy	s,S-policy	Optimization model
ESR [kWh]	697.52	778.13	627.51	587.74	1122.24
ESG [kWh]	150.45	144.33	111.04	165.20	0.00
Relative ESR usage [%]	82	84	85	78	100
Job processing rate [%]	93	93	93	93	93
Machine postponement	0	0	3	4	0
Compressor delay	0	0	3	4	0
Forklift delay	0	0	0	0	0

Table 4.7: Charging policy comparison with two periods demand length and consistent forklift selection.

KPI	t,q-policy	t,S-policy	s,q-policy	s,S-policy	Optimization model
ESR [kWh]	1156.59	1437.50	715.15	756.91	1876.63
ESG [kWh]	262.92	313.68	132.81	194.00	0.00
Relative ESR usage [%]	81	82	84	80	100
Job processing rate [%]	73	93	47	47	93
Machine postponement	183	24	602	368	0
Compressor delay	183	24	602	368	0
Forklift delay	0	0	0	0	0

the job processing rate. Nevertheless, the by far best performance is again achieved when leaving the charging decisions to the optimization model.

Of course, machine postponements could be reduced by a decrease of compressor- and forklift delays. This could be achieved by a company through new equipment types that have a higher maximum inventory capacity (inv_{max}), which would then also require fewer charging activities. In the case of the forklifts, this effect could also be achieved by adding further forklifts to the fleet. In an extreme example, where the intralogistics equipment's inventory capacity equals the overall demand de_t for the entire simulation

Table 4.8: Charging policy comparison with three periods demand length and consistent forklift selection.

KPI	t,q-policy	t,S-policy	s,q-policy	s,S-policy	Optimization model
ESR [kWh]	1204.82	1528.02	406.70	983.83	2275.24
ESG [kWh]	409.05	420.39	58.31	218.84	0.00
Relative ESR usage [%]	75	78	87	82	100
Job processing rate [%]	53	60	20	40	73
Machine postponement	421	219	1186	901	158
Compressor delay	421	202	1186	723	158
Forklift delay	0	17	0	178	0

horizon, no charging would be required at all from which all charging policies would result in an identical maximum job processing rate and merely differ in the share of *ESR* and *ESG* electricity consumption.

To summarize, the computational experiments have demonstrated that charge interval parameterization, the implementation of a static charging policy or an intralogistics charging optimization model as well as the demands for intralogistics inventory exert a decisive influence on the performance of the production environment. The intralogistics charging optimization model is capable to outperform the static charging policies in all considered settings and with respect to all analyzed KPIs. Therefore, the computational experiments reveal that the intralogistics charging optimization model dominates all static charging policies, leading to significant performance benefits for an industrial company.

4.5 Conclusions

The integration of electricity-intensive intralogistics equipment has rarely been considered in the research on energy-aware production management. To close this gap, we have presented an optimization model that synchronizes intralogistics devices' charging decisions with a production schedule and the availability of renewable electricity in a power grid. Additionally, a decentral decision-making framework is proposed to orchestrate intralogistics charging decisions while taking into account the availability of sustainable electricity in the course of time. We have benchmarked our intralogistics charging optimization model against well-known static charging policies and have demonstrated that the optimization model is capable to outperform all static charging policies in every considered setting. Using the proposed model, a company can temporarily increase its electricity consumption in times of generation peaks of renewable electricity, which prevent a temporary shutdown of windmills, solar panels, etc. due to feed-in management. Implementing this decision-making methodology offers an opportunity to synchronize industrial manufacturing processes with the availability of renewable electricity, contributing to a reduction of CO_2 emissions from manufacturing processes.

Regarding future research, policy instruments that provide incentives for companies to adapt their production and intralogistics-based electricity consumption to the availability of renewable electricity generation seem promising. In addition to the considered charging decisions, the integration of energy-aware routing decisions for those intralogistics devices that perform material handling operations may be of interest too.

Acknowledgments

The authors would like to thank the Gesellschaft für Energie und Klimaschutz Schleswig-Holstein GmbH (EKSH) for promoting this project in form of a PhD scholarship.

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Chapter 5

Energy-aware coordination of manufacturing equipment in flow shop and job shop production environments with stochastic job arrival

Publication status Submitted in 2023: *Computers & Insutrial Engineering.*

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Abstract A manufacturing company's production-related decision-making is to a large extent characterized by machine scheduling and support device operations management. All these industrial equipment types consume energy, often in the form of electricity. This electricity is more and more provided by renewable energy sources such as wind and solar power. The volatility of these power sources can lead to peak periods where feed-in management is required to stabilize a power grid. In this paper, we suggest to increase local industrial energy consumption in such periods to relieve the power grid. For this, we use models that are capable of synchronizing machine scheduling activities and support device charging operations with the availability of renewable energy. We then use a decentralized decision-making platform to coordinate the decision-making of various

types of production-related equipment. By integrating a forecast for the occurrence of excessive renewable energy into this coordination platform, an opportunity is given to support environmentally oriented production decisions that avoid feed-in management actions in the power grid that surrounds the company. In a simulation study based on real-world data, we compare flow shop and job shop production environments, both under stochastically arriving jobs in such an energy-oriented setting. We furthermore introduce and examine the impact of machine-specific due date adjustment methods to achieve high processing rates and low job tardiness next to the energy-related goal. The presented approach is computationally analyzed with respect to the trade-offs of these conflicting goals in both types of production environments.

Keywords Machine scheduling; stochastic job arrival; energy awareness; event-driven demand response; job shop; flow shop

5.1 Introduction

Since industrial production equipment is in many cases operated by electrical power, industry is the largest consumer of electricity in many developed economies. For example, industry accounted for about 44 % of the net electricity consumption in Germany in the year 2021 (Destatis 2022). Increasing environmental concerns as well as rising fossil energy costs, therefore, lead to more and more energy awareness in industrial production environments.

The expansion of electricity generation from renewable energy sources like wind or solar power provides an opportunity for more sustainable electricity generation but also creates new challenges. Renewable energy generation goes along with volatility and peak rates, which constitute a threat to the stability of insufficient electricity grid infrastructure. This requires *feed-in management* actions to limit the feed-in of excessive energy and, thus, ensure a balanced electricity grid. As a consequence, less renewable energy is fed into the grid in times of feed-in management actions, even though more energy could have well been produced. Especially wind and solar power-abundant regions face the challenge of local excessive renewable electricity production. In 2021, 5,818 GWh of renewably generated electricity was lost due to feed-in management actions in Germany, which additionally resulted in corresponding claims for compensation from operators of renewable power plants of about €807 million (Bundesnetzagentur 2021). By fostering adjustable local electricity consumption, an opportunity would be given to counteract such renewable energy losses, as the electricity grid is relieved from transmitting this energy to other regions and the, thus, the corresponding infrastructure bottleneck is bypassed.

Increasing energy awareness in production environments integrates an energy perspective into a company's decision-making. All energy-consuming operations at the production floor determine a company's energy consumption profile. Energy consumption of production machines is typically determined through *job scheduling decisions* in both, job shop as well as flow shop production environments. These decisions are often made with respect to customer-oriented service objectives such as avoiding job tardiness w.r.t. due dates. But also support devices contribute to a company's energy consumption through their corresponding *recharging decisions*. Thereby, under the term support device, we subsume here all types of equipment that assists machine activities, for example, by handling material or through similar processes. To jointly consider both types of such energy consumers, we use in this paper optimization models for job scheduling decisions on production machines and for recharging decisions on support devices. However, there exists a conflict of objectives as these decisions account for service- as well as energy-related objectives. The paper at hand, therefore, adopts a decentral decision-making methodology, the so-called *production coordination platform* (PCP), to bring together and orchestrate machine scheduling and support device recharging decisions in the course of time.

With this paper, we primarily focus on the interrelations of service- and energy-related objectives in production environments where jobs arrive stochastically and each job has to be processed by several machines with a given machine routing. We contrast flow shop production environments where jobs show identical machine routings and consistent operation sequences with job shop environments where each job can have an individual machine routing and operation sequence. In what follows, we consider both such systems in the decentral decision-making environment. We examine the impact of these different production environments in a simulation that is based on real-world data. In this context, the conducted computations examine the impact of stochastic job arrival in both production environments and contrast the energy- and service-related objective functions. Furthermore, we introduce and analyze machine-specific due dates to demonstrate their influence regarding the decentral decision-making process.

The paper is organized as follows: Section 5.2 provides an overview of the relevant literature on energy awareness in production environments. In Section 5.3, the proposed production environment, the model formulations, and the PCP are described. The general simulation study setting is introduced in Section 5.4 while Section 5.5 aims at the computational experiments, which analyze the impact of stochasticity in job arrivals and the production environment on the performance of the PCP. Conclusions are provided in Section 5.6.

5.2 Literature review

Environmental concerns and increasing energy costs make energy awareness an increasingly important aspect of industrial manufacturing giving rise to a large number of publications over the last years. Energy awareness incorporates energy-related aspects in production-related decision-making. In this line of thought, demand-side management aims to adjust production energy consumption to certain external signals. The literature differentiates between price-driven and event-driven demand response approaches (Biel and Glock 2016). While price-driven demand response considers energy prices as external signals, event-driven demand response states reactions to particular events like renewable energy peak generation due to high wind levels or sun-intensive periods. Furthermore, the large number of energy-aware publications can be categorized based on the considered planning problems into various research streams with detailed literature surveys being available for all of them. While Gahm et al. (2016) solely classify machine scheduling models, Biel and Glock (2016) focus on articles in the context of master production scheduling, capacity planning approaches, and lot-sizing. Bänsch et al. (2021) link both these reviews and provide an updated as well as extended literature overview for this field of research. Terbrack et al. (2021) review the literature with a particular focus on energy-aware models in hierarchical production planning.

With regard to our study, the following papers are of particular relevance as they consider multiple objectives within energy-aware production scheduling. In a price-driven demand response setting under a time-of-use setting, Heydar et al. (2022) put emphasis on energy-efficient unrelated parallel machine scheduling and propose a method from the field of approximate dynamic programming to take into account that jobs arrive at the system randomly. The approach minimizes the schedule makespan as well as total energy costs, where energy costs include the cost of energy consumption of machines for switching on, during processing, and in an idle state. Mansouri et al. (2016) consider a two-machine sequence-dependent permutation flow shop. They analyze the trade-off between minimizing makespan, a service level measure, and total energy consumption. Different machine speed levels with various energy consumption levels allow for exploring the potential of energy saving in the considered manufacturing system. The authors develop a mixed integer linear multi-objective optimization model to identify the Pareto frontier comprised of makespan and total energy consumption. A construction heuristic is proposed for solving the problem. Ruiz Duarte et al. (2020) focus on a manufacturing system with a single-item manufacturing process and consecutive production stages with the aim to integrate various renewable energy sources. The proposed optimization model obtains a production schedule that matches the onsite renewable energy supply with an energy storage system and the electricity grid as a backup. To counter renewable energy generation uncertainties, a two-stage robust optimization model is proposed. For solving this formulation, a nested Column-and-Constraint Generation algorithm is applied. Lang et al. (2016) take a look into agent-based automated negotiation mechanisms for decentralized scheduling problems with heterogeneous machines that process competing jobs. The objective is to minimize tardiness cost, machine operating cost, or energy cost. Rubaiee and Yildirim (2019) focus on single-machine scheduling with job preemption in a time-of-use energy price setting in order to minimize total completion time and total energy cost. Karimi and Kwon (2021) consider joint on-site renewable energy production, energy storage, and energy-aware production scheduling and the impact on energy cost as well as makespan. The conducted experiments reveal cost-savings and performance effects as a result of proper system configuration. Wang et al. (2020) propose a stochastic optimization model with multiple objectives and two stages for flow shop scheduling. In a time-of-use electricity price setting, the authors integrate on-site renewable energy generation with energy storage. The approach of Materi et al. (2021) adjusts CNC machine cutting speed and aims at energy costs and CO_2 emissions reduction by integrating photovoltaic plants and battery storage. Biel et al. (2018) emphasize on-site renewable energy generation stochasticity in a flow shop scheduling environment. Under a time-of-use energy price setting, they aim to minimize both, total weighted flow time and energy costs. In accordance, Subramanyam et al. (2020) additionally account for onsite renewable energy generation in a flow shop production environment. They propose a two-stage mixed-integer optimization model to minimize energy costs. While the first stage minimizes the per-year energy consumption with respect to job throughput requirements, the next stage considers the sizing of wind turbines, solar panels, and battery units to meet the electricity demand.

The survey of Bänsch et al. (2021) reveals streams of recent research and identifies future research topics with regard to energy-aware machine scheduling. Besides on-site renewable energy generation, dynamics, rescheduling, and usage of multiple forms of energy, a need for combined production scheduling and supporting processes, like for example material handling, is identified. In this context, Liu et al. (2019) consider crane processes for the transportation of workpieces within a flexible job shop scheduling problem. Their approach minimizes the total cost of consumed energy and schedule makespan. Hemmati Far et al. (2019) consider flexible manufacturing cells with industrial robots. Automated guided vehicles (AGVs) transport material between manufacturing and storage areas. The model aims to minimize production and transport costs under a time-of-use electricity tariff to account for the energy consumption of moving AGVs as well as for job tardiness. With a wider focus, Wang (2019) integrate vehicle routing for final product distribution with single machine scheduling in order to minimize total CO_2 emissions. The approach proposed by Yun et al. (2022) minimizes production electricity costs under a time-of-use electricity tariff. The novelty is the integrated demand response model for scheduling in a manufacturing environment in combination with a material handling recharging system. The authors apply a price-driven demand response and additionally account for material handling equipment recharging decisions.

This literature review has shown so far that a large number of studies focused on price-driven demand response approaches. Research on event-driven demand response is clearly lacking. One study in this regard is Scholz and Meisel (2022), who suggest event-driven demand response to counteract feed-in management actions at a regional level in times of peak renewable energy generation. A price-driven demand response is not appropriate in this context as electricity prices are determined for an entire renewable energy market, from which they cannot reflect local renewable energy generation peaks and feed-in management actions at a regional level. The authors propose an agent-based decentral decision-making platform to incrementally plan and coordinate machine scheduling decisions with support device recharging decisions. Scholz and Meisel (2022) exclusively consider a job shop production environment with a known and given set of jobs. In contrast, the paper at hand extends on Scholz and Meisel (2022) by comparing job shop and flow shop environments for which jobs are not known at the beginning of the planning horizon but arrive stochastically over time. The jobs are complex in that they exhibit (job-specific) machine routings involving multiple operations. We compare these production environments within a simulation study with respect to their performance for both, energy- and service-oriented objectives. Based on the above literature review, such a comparison of flow shop and job shop systems with regard to energy and service objectives has not been conducted yet, even though it is of practical relevance to better understand the performance of various production systems in the context of energy-aware production management.

5.3 Production environments' decision-making and coordination platform

In this section, an event-driven demand response approach in a job shop as well as a flow shop production environment, both with stochastic job arrivals, is studied. First, in Subsection 5.3.1, we describe the production environment with the underlying mathematical model formulation. Then, Subsection 5.3.2 provides an algorithm that specifies the decentral decision-making, which coordinates numerous production equipment units within a rolling time horizon. Finally, Subsection 5.3.3 introduces methodologies for machine-specific due dates.

5.3.1 Problem specification and model formulation

We consider here an energy-intensive production environment in an event-driven demand response setting. A simplified version of the problem was investigated by Scholz and Meisel (2022), where a given set of jobs had to be processed on a set of machines without a predetermined machine order. In the paper at hand, we extend the problem towards more realistic production environments by integrating stochastic job arrivals and machine precedence relations for jobs that resemble both, job shop as well as flow shop production environments.

The equipment in this production environment is subdivided into two general types. One equipment type refers to the machines that execute the production jobs whereas the second equipment type are support devices that assist in terms of material handling and ensure production factor supply to the machines. We describe the decision-making for the machines formally and present the corresponding optimization model whereas the support device recharging decisions are merely described verbally afterwards to avoid redundancies in this paper and with Scholz and Meisel (2022).

The production environment processes stochastically arriving jobs J. Each job $j \in J$ consists of an individual set of operations that have to be processed in a predefined sequence. The machine environment consists of n machines and processing of a certain operation is dedicated to a fixed machine out of this set. With this, each job exhibits individual machine precedence relations. We assume that each machine is capable to perform a single job at a time and operations are processed non-preemptively. Based on discrete time periods, the time horizon of interest is denoted by T. Each job exhibits an individual time window for being processed. The time window starts with an arrival date a_j at which the first operation can be started at the earliest. It ends with a due date d_j that represents the job's preferred time of completion. We consider the due date as a soft constraint, meaning that tardy completion of a job beyond d_j is allowed but such tardiness should be minimized to avoid dissatisfaction of customers.

The production coordination platform (PCP) that is explained in the next subsection coordinates the decision-making of machines and support devices by having each such equipment unit solve its own decision model whenever certain events take place in the production environment. Due to this, we will subsequently focus on a single machine's decision-making model, similar to the one proposed by Scholz and Meisel (2022), which is triggered each time that the machine has finished those jobs that it scheduled in its preceding planning run. From the perspective of such an individual machine, processing a job j is identical to processing the job's corresponding operation that is dedicated to this machine. Due to this, we do not need to distinguish jobs and operations in the model and, for reasons of simplicity, we just refer to 'jobs' rather than 'operations' in the following. The machine-dependent processing time for job j on the considered machine is given by p_j and measured in periods. The corresponding machine electricity consumption for this operation is reflected by rate q_j. Furthermore, the dichotomous parameter re_t represents a forecast which indicates for each period $t \in T$, whether feed-in management actions are necessary ($re_t = -1$) or not ($re_t = 1$) from the perspective of the power grid. In other words, in periods $re_t = -1$ feed-in management actions (FMA) reduce the generation of electricity to stabilize the power grid. In such periods, the considered company could well *increase* its local consumption to retrieve more energy from the grid and avoid such FMA's (and the corresponding loss of renewable energy that could actually be generated in that period). Periods with no need for feed-in management actions are indicated by $re_t = 1$. Relating production decisions and their energy consumption to parameter re_t constitutes the event-driven demand response in our proposed approach.

The decisions of the machine under consideration are then expressed through binary variables $x_{j,t}$, equal to 1 if the processing of job j is started in period t, 0 otherwise, and binary variables $y_{j,t}$, equal to 1 if job j is processed in period t, 0 otherwise. Depending on these decisions, the tardiness ta_j of job j is determined if that job ends beyond its due date. All notation is summarized in Table 5.1.

Table 5.1: Notation for machine job scheduling.

Sets	
J	Set of released jobs for the machine under consideration
T	Set of periods
Parameters	
a_j	Arrival date of job $j \in J$ [period]
d_j	Due date of job $j \in J$ [period]
p_j	Processing time of job $j \in J$ for the machine under consideration
q_j	Power consumed by job $j \in J$ per period processing time for the machine under consideration
re_t	Dichotomous parameter, with $re_t = -1$ if feed-in management action in period t (*FMA*-period) is indicated, otherwise $re_t = 1$ (regular period without feed-in management action)
Decision variables	
$x_{j,t}$	Binary variable, equal to 1 if processing job j starts in period t, 0 otherwise
$y_{j,t}$	Binary variable, equal to 1 if job j is processed in period t, 0 otherwise
ta_j	Job tardiness, measured as period-based due date exceedance of job j

The model for the individual decision-making of a machine is then stated as follows:

$$\min \rightarrow TA = \sum_{j \in J} ta_j \tag{5.1a}$$

$$\min \rightarrow CT = \sum_{j \in J} \sum_{t \in T | a_j \leq t} x_{j,t} \cdot (t + p_j - 1) \tag{5.1b}$$

$$\min \rightarrow ERE = \sum_{j \in J} \sum_{t \in T | a_j \leq t} y_{j,t} \cdot q_j \cdot re_t \tag{5.1c}$$

$$\sum_{t \in T | a_j \leq t} x_{j,t} = 1 \qquad j \in J \tag{5.2}$$

$$\sum_{t \in T | a_j \leq t} y_{j,t} = \sum_{t \in T | a_j \leq t} x_{j,t} \cdot p_j \qquad j \in J \tag{5.3}$$

$$\sum_{\tau \in T | t \leq \tau \leq t + p_j - 1} y_{j,\tau} \geq x_{j,t} \cdot p_j \qquad j \in J, t \in T \tag{5.4}$$

$$\sum_{j \in J | r_j \leq t} y_{j,t} \leq 1 \qquad t \in T \tag{5.5}$$

$$ta_j \geq \sum_{t \in T | a_j \leq\ t} x_{j,t} \cdot (t + p_j - 1 - d_j) \qquad j \in J \tag{5.6}$$

$$ta_j \geq 0 \qquad j \in J \tag{5.7}$$

$$x_{j,t}, y_{j,t} \in \{0, 1\} \qquad j \in J, t \in T \tag{5.8}$$

In order to analyze service as well as energy targets in the decision-making, the model comprises three objectives (5.1a), (5.1b), and (5.1c). The first objective aims to meet customer appointments with a total job tardiness minimization (*TA* in (5.1a)). Tardiness results when the completion time of job j for the machine under consideration exceeds the corresponding due date d_j. In a similar regard, the second objective (*CT* in (5.1b)) represents the minimization of the overall completion time of all jobs to enforce their finishing as soon as possible. The third objective is related to the consumption of (excessive) renewable energy (*ERE* in (5.1c)). It aims to shift production-related energy consumption from regular periods ($re_t = 1$) into *FMA*-periods ($re_t = -1$) to consume more energy in periods that suffer from feed-in management actions. In our later experiments, we bring these objectives in an order of priority and solve them hierarchically in terms of a lexicographical objective function. This allows us to understand how these objectives impact decision-making and whether they are conflicting or in line with each other.

The following constraints guarantee the feasibility of the machine scheduling solutions. Constraints (5.2) ensure that job j is started exactly once on the machine under consideration. Constraints (5.3) enforce that the processing of job j takes exactly p_j periods on the considered machine. Constraints (5.4) guarantee processing without preemption. Constraints (5.5) make sure that the machine processes at most one job per period t. Constraints (5.6) and (5.7) compute the tardiness for objective function (5.1a). Constraints (5.8) assure the binary character of variables $x_{j,t}$ and $y_{j,t}$.

The operations of the machines are accompanied by support devices (e.g. forklifts for material handling) that need to be coordinated with the machines' production schedule in order to avoid disruptions to the production processes. This coordination is ensured through the subsequently presented PCP. The support devices themselves have to make recharging decisions in order to be able to suitably supply the machines. More formally, the jobs scheduled on the machines constitute for a considered support device a service demand that consumes the support device's charging level at a rate of de_t in periods

$t \in T$. Furthermore, the support device has an initial charging level inv_0 in period 0 and a possible maximum charging level inv_{max}. Then, recharging decisions are necessary from time to time to have a sufficient charge level that allows for fulfilling the service demands. These charging decisions can be made according to service objectives or energy objectives like in the machine model presented above. A corresponding optimization model for the support devices can be found in Scholz and Meisel (2022). We abstain from repeating this model here.

5.3.2 Production coordination platform

A production coordination platform (PCP) orchestrates the individual decision-making processes of machines and support devices, where each machine and each support device exhibits its individual decision-making authority. An in-depth introduction to the PCP's fundamentals is provided in Scholz and Meisel (2022). For the subsequent computational experiments, we simulate the behavior of the PCP in accordance with the procedure that is outlined in Algorithm 2. This algorithm was initially introduced with a focus on support device recharging in Scholz (2023) and is modified here for our later comparison of flow shop and job shop production systems. According to this algorithm, a priority queue of requests for production scheduling decisions on machines (M), recharging decisions on support devices (SD), as well as job arrival (JA) events incrementally builds a schedule within a rolling time horizon. The priority queue and all relevant input data are initialized in Lines 1 to 6, where each of the initially known requests $e \in E$ is placed according to the period at which it takes place. The actual priority queue procedure starts at line 7. Here, the request that occurs next is identified in line 8. According to the event-driven demand response, a forecast of the feed-in management actions in the next periods is received in line 9. Next, the algorithm differentiates whether the current priority queue request e belongs to a machine (see line 10), a support device (see line 28), or a new job arrival (see line 33).

In the event of a machine request (line 10), the PCP first releases a number of arrived jobs to the machine (see lines 11 - 12). This number of *released jobs* is a parameter that controls the work-in-progress of the machine and is later analyzed in detail in the experiments in Section 5.5.1. In order to schedule new jobs on the considered machine, adequate support device charging levels are necessary to cover the upcoming demand de_t in subsequent periods t. In case this requirement is not met, the machine request is delayed to a later period in order to recharge the support device in the meantime, see lines 14 - 17. Otherwise, the machine is able to proceed with its production planning,

Algorithm 2 PCP decision-making process.

```
E ← M ∪ SD ∪ JA          ▷ set of request types (machine, support device and job arrival)
A = initial jobs; R = [ ]; P = [ ]          ▷ list of arrived-, released- and processed jobs
Q ← priority queue()          ▷ initialize priority queue
for e ∈ E do
    e.request ← initial request period          ▷ assign initial request period
    Q.put(e)          ▷ place request in priority queue
while Q ≠ ∅ do          ▷ priority queue procedure
    e ← Q.get()          ▷ select next request from priority queue
    retrieval of feed-in management action forecast re_t
    if e refers to type M then          ▷ request type 'machine'
        if |R|< job amount then          ▷ based on 'job amount'-parameterization
            move earliest jobs from A to R ▷ First In First Out (FIFO) discipline to respect
            job arrival dates
        compare required capacity with support device charging level
        if insufficient support device charging level then
            e.request ← next request period          ▷ postpone machine request
            sd.request ← next request period          ▷ define next request for recharging
            Q.put(sd)          ▷ insert sd into priority queue
        else
            retrieve machine dependent operation parameters p_j and q_j
            solve model (5.1a) - (5.8)          ▷ solve machine scheduling model
            transmit production decisions to machine
            update de_t          ▷ derive support device demand from production decision
            for j ∈ R do
                if job j's final operation was executed then
                    R.remove(j)          ▷ remove job from list of released jobs
                    P.append(j)          ▷ add job to list of processed jobs
            e.request ← next request period          ▷ next request when machine runs idle
    if e refers to type SD then          ▷ request type 'support device'
        retrieval of support device demand de_t in period t
        call support device optimization model          ▷ see Scholz and Meisel (2022)
        transmit recharging decisions to support device
        e.request ← next request period          ▷ next request when recharging is necessary
    if e refers to type JA then          ▷ request type 'job arrival'
        if production environment equals flow shop system then
            define new job with consistent and identical machine precedence relations
        if production environment equals job shop system then
            define new job with random and job-specific machine precedence relations
        A.append(new job)
        e.request ← next request period with X ∼ Exp(λ)          ▷ next job arrival request
    Q.put(e)          ▷ put follow-up request in priority queue
```

see lines 19 - 21, where new jobs are scheduled through the optimization model and the corresponding decisions are given as instructions to the machine. The newly scheduled jobs then constitute the new demands for support devices, which is reflected by updating de_t in line 22. Furthermore, all jobs that are finished are transferred from the list or released jobs to the list of processed jobs, see Lines 23 - 26. Line 27 completes the request and defines the follow-up request.

If the event refers to a support device that requests to recharge (line 28), the demand de_t for upcoming periods t is derived from the machine schedules (line 29). Afterward, the support device optimization model is solved (see line 30), and line 31 updates the support charging schedule. To complete this request, line 32 defines the follow-up request, for example, to trigger a support device again as soon as the next recharging decision becomes necessary.

In the event of a new job arrival (line 33), lines 34 to 37 differentiate the underlying production environment. In the case of a flow shop system, each new arriving job receives an identical machine routing (M1, M2, etc.) and corresponding identical production-related data (p_j, q_j), see lines 34 and 35. In the case of a job shop system, new arriving jobs exhibit random and job-specific machine routings with individual production-related data (p_j, q_j), see lines 36 and 37. The list of arrived jobs A is then extended by the new job. Afterward, the next request period is defined according to the exponentially distributed job inter-arrival time $X \sim Exp(\lambda)$.

The updated or new request is finally inserted into the priority queue (line 40).

5.3.3 Due date adjustment methodologies

As mentioned in Section 5.3.1, each job j appears to the system at an individual stochastic arrival date a_j (specifying the earliest period processing can be started) and has a due date d_j, which refers to the preferred time of completion. Due to the decision authority of each individual machine and the decomposition of the overall machine scheduling problem into individual decentral single machine scheduling problems in a rolling horizon manner, due dates are of particular relevance for the decision-making. However, providing the final job due dates d_j to all machines raises the challenge that upstream machines are hardly restricted by those due dates whereas downstream machines may unavoidably generate tardiness, as there is not enough remaining buffer time left before that due date is reached. This is because preceding machines observe quite a far-away deadline for their operations and do not anticipate the potentially arising tardiness of subsequent machines. This phenomenon applies in particular to the energy-related *ERE*-objective, as there is no time component in the objective function that would foster early completion of operations. Due to this, a job's operation on an early machine might be scheduled very late just to benefit from excessive renewable energy at that time. Later machines then fail to meet the due date when scheduling their operations for that job. To counteract this, we will introduce machine-specific due date adjustments and later analyze their role when optimizing for energy- and service-oriented goals. In particular, we focus on three different due date adjustment methods. The benchmark is the so-called *no adjustment* method where all machines are provided with the final job due date d_j. With the *equal division*, we introduce machine-specific due dates that are calculated for the operation of each machine individually. In this setting, the length of the processing time window $d_j - a_j + 1$ of job j is equally divided among all machine operations, such that $\frac{d_j - a_j + 1}{|O_j|}$ time units are available per machine, where $|O_j|$ refers to the number of operations (machines) of job j. With this formulation, each machine performing a single operation receives an individual due date with respect to the machine operation order and the allowed time units. At the same time, there is no differentiation between long or short machine processing times. Based on that, the *weighted division* takes differences in the processing time of the individual machines into account. With this, a machine exhibiting a longer operation processing time receives a larger share of the processing time window $d_j - a_j + 1$ than a machine showing a shorter operation processing time. More precisely, the sum of job j's processing times over all machines is denoted as $\widetilde{p_j}$. With respect to a job's machine-specific processing time p_j, the individual machines' share of the time window is then computed as $\frac{p_j \cdot (d_j - a_j + 1)}{\widetilde{p_j}}$.

5.4 Simulation study setting

This section explains the general setup for the simulation system that is used afterward to study flow shop and job shop systems with stochastic job arrival and decentralized PCP decision-making under environmental- and service-oriented objectives. We focus on a production environment with stochastic job arrival, where the job inter-arrival time X is a random variable following an exponential distribution $X \sim Exp(\lambda)$ with $E(X) = \frac{1}{\lambda}$. For example, in a setting with $\lambda = 0.1$ the job inter-arrival time $X \sim Exp(0.1)$ has an expected value of $E(X) = \frac{1}{0.1} = 10$, corresponding to an expected new job arrival every 10 periods.

Jobs have to be processed by several machines with known operation sequences and processing times p_j. Job arrival dates a_j correspond to the aforementioned exponentially distributed stochastic job arrival. Corresponding due dates are computed as $d_j = a_j +$

$\sum_{j \in J} p_j \cdot \omega$ where ω is a parameter that controls the tightness of the processing time window. With $\omega = 1$, the time between the arrival date and the due date equals exactly the processing time of all required operations. To give some more flexibility, we set $\omega = 2$, which corresponds to a time window twice as large as the required processing time.

The computational experiments will differentiate between a job shop- and a flow shop-oriented production environment, following the definition of Pinedo (2016). This differentiation is reflected by the characteristics of the corresponding jobs. For the flow shop production environment, all jobs reveal identical machine routings beginning on machine M1, then machine M2, and so on. In addition to that, the processing times p_j, as well as energy consumption rates q_j are identical on the machines for all jobs $j \in J$. On the contrary, the job shop environment is characterized by jobs that reveal individual machine routings where each job visits each machine at most once. Furthermore, the jobs have individual machine-dependent processing times p_j and energy consumption rates q_j.

The simulation study is inspired by a metal processing medium-sized company from northern Germany's federal state of Schleswig-Holstein, a region with a high potential for the generation of renewable wind power. The company's production environment includes two production equipment types with five machines and three support devices. Table 5.2 comprises the machines' energy consumption rates that were derived from this company. The job processing times p_j are set constantly to 3 periods in the flow shop production environment whereas they are drawn from the range $[1 - 5]$ in the job shop production environment.

Table 5.2: Machines' energy consumption rates.

	Flow shop	*Job shop*
Machine 1 [W]	$1,808$	$1,756 - 1,847$
Machine 2 [W]	$1,756$	$1,132 - 1,808$
Machine 3 [W]	$15,824$	$7,912 - 23,737$
Machine 4 [W]	320	320
Machine 5 [W]	$5,505$	$3,701 - 10,051$

As support devices, the considered company operates two electrified forklifts and one air pressure tank. The forklift's charging level consumption for supporting processing of job j in the job shop production environment is drawn from the range $[1,400; 2,925]$ based on European Norm 16796. In the flow shop environment, we set this value constantly to $2,200$. For the air pressure tank, the consumption rate (measured in liter of compressed air) is drawn from the range $[500, 1000]$ in the job shop environment and set to 500 in the flow shop environment. The electrified forklifts are capable to recharge 923 Wh to the battery per period whereas the compressor stores $2,000$ l into the air pressure tank per period. Each period equals 15 minutes, which is a typical electricity tariff-related time interval. The PCP computes the demand rates de_t of the support devices as a result of the job scheduling. In 2021 Schleswig-Holstein reveals approximately 66% *FMA*-period occurrence (Schleswig-Holstein Netz AG 2021), which serves as a basis for setting the feed-in management parameters re_t. The conducted simulations span a time horizon of 640 periods, which corresponds to 20 working days with 8 hour shifts. The individual look-ahead horizon of a request in the PCP's rolling horizon planning is set to 64 periods. All computational experiments are performed on an Intel Core i7 with a 2.5 GHz CPU and 32 GB memory. The PCP is implemented in Python 3.7 using the libraries *queue, numpy, pandas*. In order to solve the involved optimization models, *doopl.factory* and the CPLEX 12.9.0 solver are applied.

5.5 Computational experiments

While Section 5.5.1 will present a parameterization and general findings based on the stochastic job arrival, Sections 5.5.2 to 5.5.5 provide insights into various objective combinations contrasting energy- and service-related goals in flow shop and job shop production environments.

5.5.1 Production environment parameterization

It is to be expected that the arrival rates of jobs in the stochastic environment have a strong impact on the performance of the production system in general but also on the solution of the individual subproblems from Section 5.3.1, especially as a large number of jobs may not be processable within the given time horizons. To cope with this, it is necessary to decide on the number of jobs that are released to a machine each time its scheduling procedure is triggered by the PCP. We call this parameter the '*job amount*' and test various values for it under varied job arrival rate parameters λ. The performance of these parameter settings is measured in terms of the *job processing rate*, which represents the ratio of jobs that are finally processed by the system at the end of the simulation horizon.

Figures 5.1 and 5.2 illustrate for job shop and flow shop production, respectively, the achieved job processing rates where the parameter job amount is varied in the range 1 to 20 and job inter-arrivals follow five settings with $\lambda = 0.2$ to 1.0. For each such setting

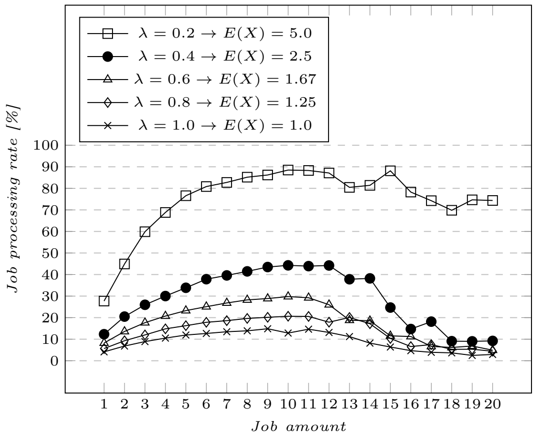

Figure 5.1: Job amount parameterization in job shop production environment.

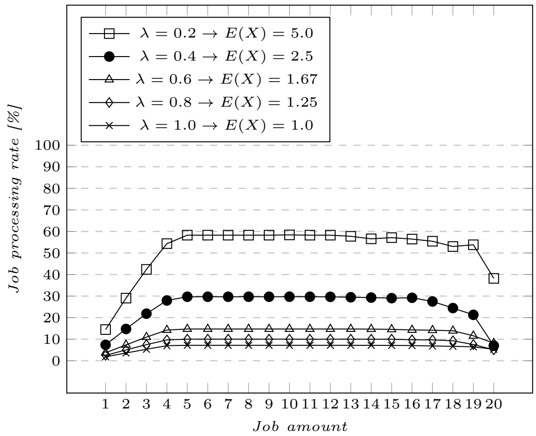

Figure 5.2: Job amount parameterization in flow shop production environment.

with *ERE* objective, we have conducted five independent simulation runs and report the average job processing rate over these runs.

With regard to the job shop results in Figure 5.1, all scenarios have in common that job processing rates first increase with rising job amount and then reach a maximum. Beyond this, a further rise of the job amount parameter decreases the job processing rate again. This is explained by the fact that a too large number of released jobs cannot be processed by the machines as the capacities of the support devices are then insufficient but cannot be recharged within a machine's scheduling run. We observe that the highest inter-arrival time of $E(X) = 5.0$ ($\lambda = 0.2$) achieves the highest job processing rate of about 90% if the job amount is set to 10. An explanation why this system does not reach a 100 % processing rate is that it is impossible to complete jobs that are released close to the end of the simulation time horizon (end-of-horizon effect). For lower inter-arrival times (larger values of λ), the system cannot catch up in processing the quickly arriving jobs, which leads to significantly lower job processing rates. While $\lambda = 0.4$ reveals a maximum processing rate of around 44 %, $\lambda = 0.6$ goes along with approximately 30 %, and $\lambda = 0.8$ exhibits only 21 %. If one job arrives each period on average ($\lambda = 1.0$), the system can only process 15 % of the jobs, which clearly reveals the overload of the production environment. Nevertheless, we observe that almost all settings perform best if the parameter job amount is set to 10.

Figure 5.2 considers the flow shop environment. It becomes apparent that the processing rate is lower compared to the job shop production environment, which can be explained by the higher number of operations per job, as processing is necessary on all machines for each job. All scenarios have in common that they reveal comparably low yet increasing processing rates for job amounts up to 5. From there on, processing rates are quite constant over a long range of job amount values. For example, while $\lambda = 0.2$ reveals a maximum processing rate of approximately 60 % for job amounts within the range of 5 to 16, $\lambda = 0.4$ goes along with approximately 30 % within the same range. This is due to the flow shop characteristics with identical processing times for the jobs and reveals that such a system is less sensitive to the setting of the parameter compared with the job shop environment.

In general, the conducted calculations reveal that the proposed PCP is capable to handle stochastic job arrivals. In addition, an increasing job arrival rate can lead to lower job processing rates as the machines reach their limits and cannot keep up with the fast successive job arrivals. Apart from that, it becomes clear that the job amount released to the machines is an essential parameter with a major influence on the PCP's results. With a focus on the $\lambda = 0.2$ job arrival, the following computations will base on a job amount of 10 as this achieved maximum job processing rate within almost all investigated settings.

5.5.2 Energy performance indicators under service-orientation

In this experiment, we will consider the service-oriented *TA*-objective in both production environments and the impact of the due date adjustment methods on energy and service performance indicators. For this, 20 simulation runs for each production environment and each due date adjustment method are conducted. Starting with Figure 5.3, we present our results as box plots where $\times$ marks the average, the horizontal line within the box the median, and the first and third quartiles (25^{th} and 75^{th} percentile) are the boxes lower and upper limit. The lines extending the boxes show the variability outside the first and third quartiles. Data outliers that differ significantly from the rest of the data are plotted as individual points. Figure 5.3 shows the *FMA*-rate, which is the share of job processing times that take place in *FMA*-periods. The figure reveals that all due date adjustment methods perform similarly with *FMA*-rates of around 67 %, meaning that two-thirds of the processing times of all jobs take place in *FMA*-periods with excessive renewable energy being available. The average job processing rate is not shown in the figure but equals 98 % for all due date adjustment methods.

Figure 5.4 shows the total tardiness over all jobs. It reveals that the 'no adjustment' approach causes by far the highest total tardiness of 705 periods. Applying the *equal division* significantly reduces this performance measure to 75 periods, a reduction of about 90 % compared to *no adjustment.* The *weighted division* is then capable of further slightly reducing the average total tardiness to 70 periods. Compared to the *equal division*, the *weighted division* is capable to obtain lower or equal tardiness in 60 % of the cases, whereas, for the remaining 40 %, the *equal division* provides lower total tardiness than the *weighted division.*

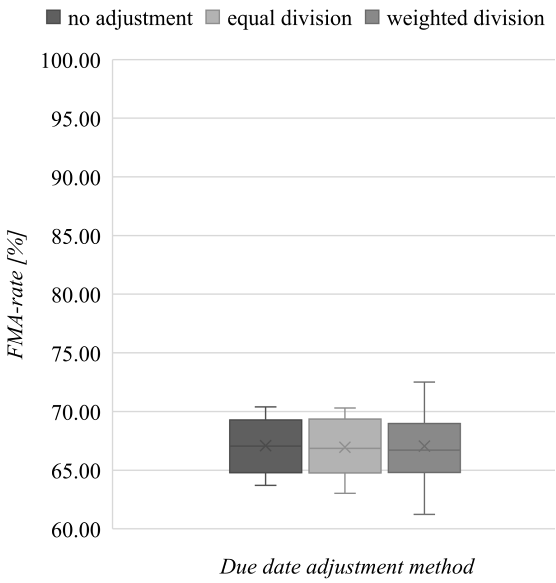

Figure 5.3: *FMA*-rate in job shop production environment with *TA*-objective.

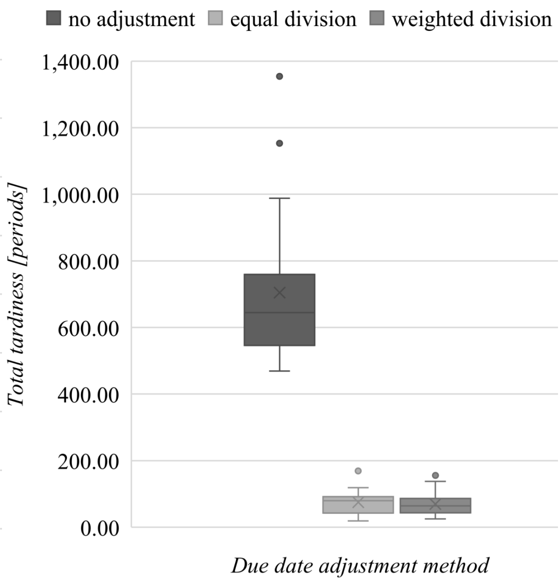

Figure 5.4: Tardiness in job shop production environment with *TA*-objective.

With respect to the flow shop environment, Figure 5.5 reveals almost identical box plots and average *FMA*-rates of around 67 % compared to the job shop setting for all due date adjustment methods. Figure 5.6 shows that the *no adjustment* method again reveals the highest tardiness with an average total tardiness of 274 periods under a job processing rate of 97 %. As in the job shop production environment, the *equal division* significantly reduces, in this case to a negligible value of just about 10 periods. In 45 % of the test runs, there is no tardiness at all. The average job processing rate stays constant at 97 %. The *weighted division* approach basically provides identical solutions as *equal division.*

Summarizing these results from an energy perspective, the *TA*-objective yields solutions with an average *FMA*-rate of around 67 %, which is in line with the average occurrence of feed-in management actions in 66 % of the simulated periods. In other words, whether or not production takes place in FMA-periods is a matter of chance because the service-oriented *TA*-objective does not strive for shifting production activities

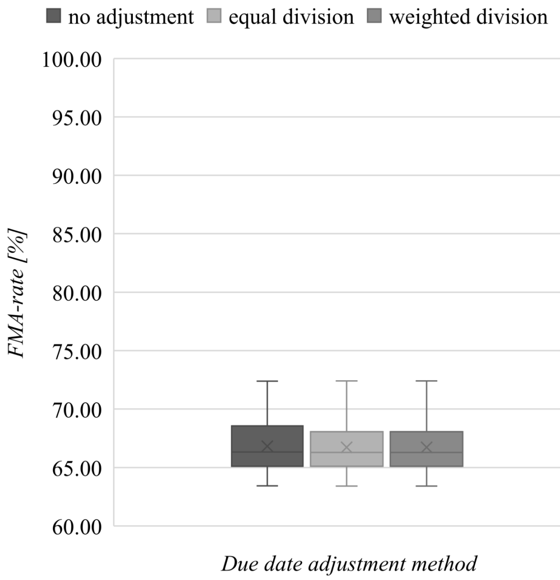

Figure 5.5: *FMA*-rate in flow shop production environment with *TA*-objective.

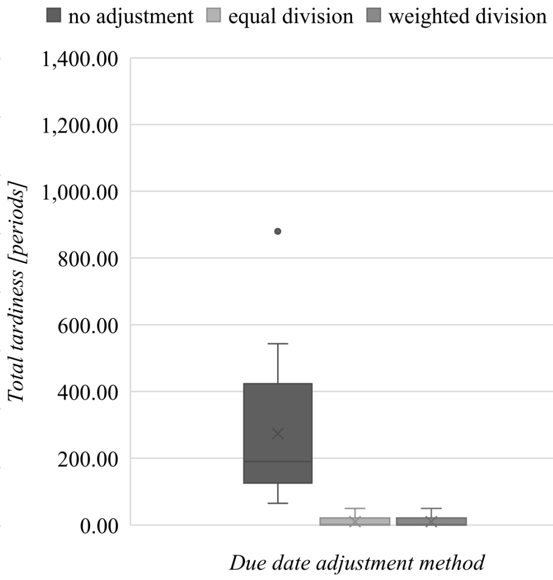

Figure 5.6: Tardiness in flow shop production environment with *TA*-objective.

into these periods. For this reason, also the choice of the due date adjustment method only exerts marginal influence on the *FMA*-rates observed in both production environments. From a service-oriented point of view, machine-specific due dates are beneficial to reduce the total tardiness in both, job shop and flow shop environments.

5.5.3 Impact of combined service-related objectives

We now integrate completion time (CT) as a secondary service-oriented goal in the lexicographical objective function to further induce early production and, thus, reduce tardiness.

Figures 5.7 and 5.8 provide the corresponding results for the job shop environment. As with the exclusive *TA*-objective, the combined TA, CT-objective exhibits comparable average *FMA*-rates of around 67 % for all three due date adjustment methods. Figure 5.8 reveals that the integration of CT as a secondary objective leads to a strong reduction of tardiness compared to the use of the sole *TA*-objective in Figure 5.4. All three, *no adjustment*, *equal division*, and *weighted division*, now show a total tardiness of just about 20 periods and achieve job processing rates of 99 %.

Figures 5.9 and 5.10 provide the results for the flow shop production environment under the TA, CT-objective combination. It becomes apparent that the integration of CT as a secondary objective leads to identical and high-quality energy- and service-

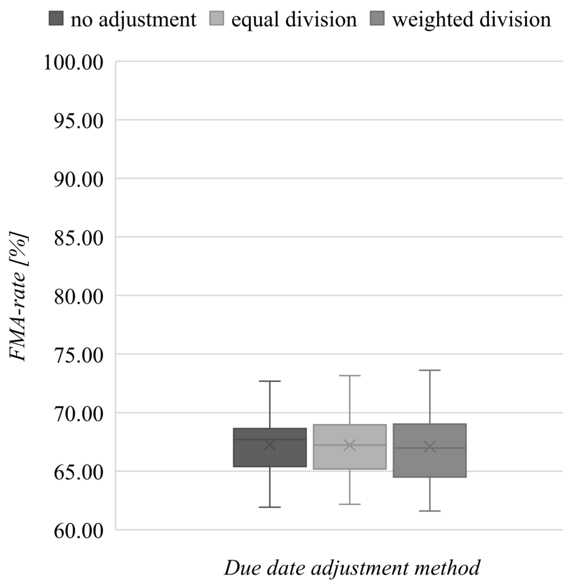

Figure 5.7: *FMA*-rate in job shop production environment with TA, CT-objective.

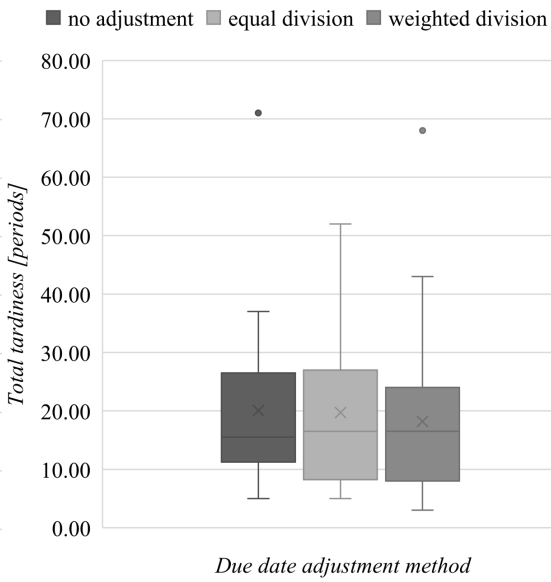

Figure 5.8: Tardiness in job shop production environment with TA, CT-objective.

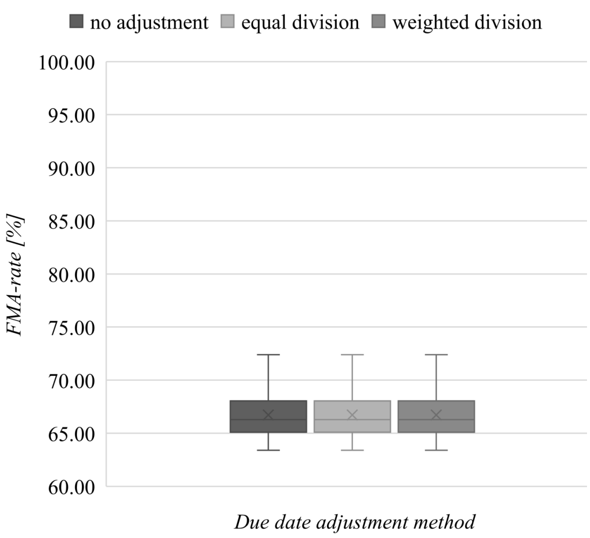

Figure 5.9: *FMA*-rate in flow shop production environment with TA, CT-objective.

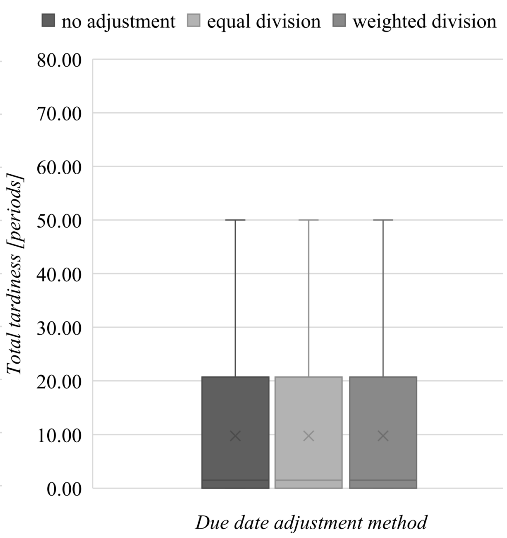

Figure 5.10: Tardiness in flow shop production environment with TA, CT-objective.

related KPIs for all three adjustment methods. The additional *CT*-integration reveals constant average *FMA*-rates of 67 % and processing rate of 99 %. It leads to a consistently low average total tardiness of 10 periods.

Summarizing these results, adding the subordinate *CT*-objective further reduces job tardiness in both considered production environments. It also effects that the solutions become much more similar for the three due date adjustment methods. As was already observed for the pure *TA*-objective, also the combined *TA, CT*-objectives lead to average *FMA*-rates of 67 %, which again shows that production takes place in *FMA*-periods purely by chance.

5.5.4 Combined service- and energy-orientation

The previous computations focused on the impact of service-oriented job tardiness minimization on energy- and service-related KPIs. In what follows, we will combine the service objective with a subordinate energy focus. The energy orientation will emphasize the event-driven demand response in the decision-making in order to push the energy consumption in *FMA*-periods while still focusing on the primary service-oriented goal to satisfy customers. For this, we combine *TA* and *CT* as in the previous experiment but add the *ERE*-objective (5.1c) as a tertiary goal in order to counteract losses of excessive renewable energy.

The average *FMA*-rate across all previous experiments was consistently around 67 %. Accounting for *ERE* as a tertiary objective in the job shop production environment now reveals a slight rise to 69 % for all due date adjustment methods, see Figure 5.11. The average total tardiness values of all three due date adjustment methods are similar under the *TA, CT, ERE*-objective and the *TA, CT*-objective, compare Figures 5.12 and 5.8. For the flow shop environment, integrating *ERE* as a tertiary objective exhibits an even lower relative increase in the *FMA*-rate from 67 % to just 68 % and no change in the tardiness values. The figures are omitted here for reasons of brevity.

To summarize, a subordinate tertiary *ERE*-orientation in combination with the service-oriented primary *TA* and secondary *CT* objectives has almost no additional potential to exploit the availability of excessive renewable energy and counteract feed-in management actions.

5.5.5 Energy orientation in an event-driven demand response setting

So far, we mainly focused on service orientation with only a subordinate energy consideration. In what follows, we will emphasize energy orientation and consider service

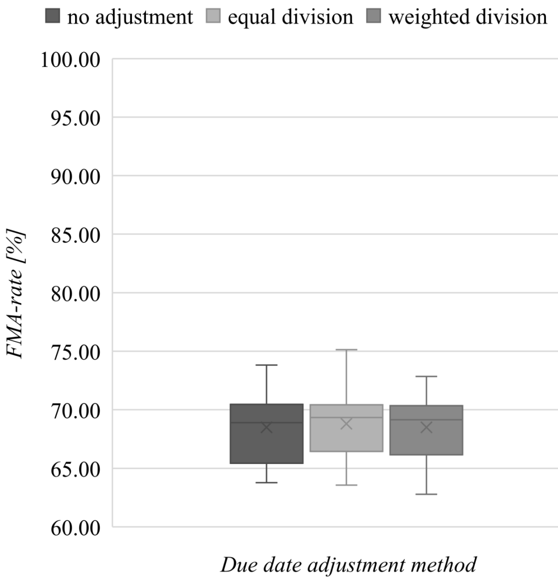

Figure 5.11: *FMA*-rate in job shop production environment with *TA, CT, ERE*-objective.

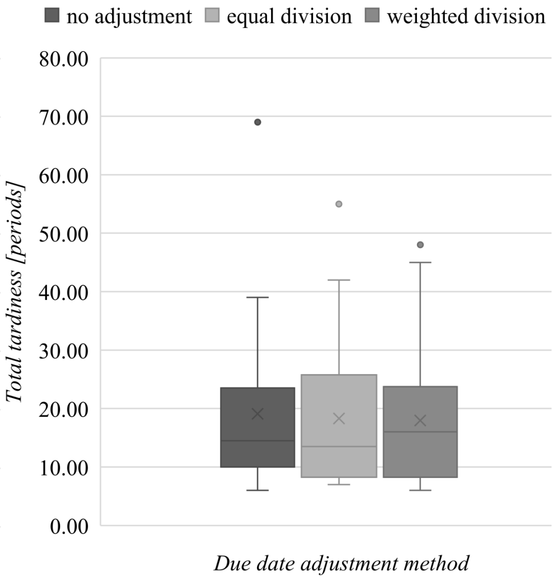

Figure 5.12: Tardiness in job shop production environment with *TA, CT, ERE*-objective.

orientation as a subordinate goal in the hierarchical objective function. Focusing on energy orientation leads to the *ERE, TA, CT*-objective combination. Here, the primary goal is to schedule jobs such that their processing consumes as much energy during *FMA*-periods as possible. The subordinate secondary and tertiary service-oriented goals are to minimize total tardiness and overall completion time.

Through this change in the scope of the planning, we now reach an *FMA*-rate of almost 100 % in both, the job shop and the flow shop environment, see Figures 5.13 and 5.14. These figures summarize the achieved job processing rates and *FMA*-rates for all considered objective combinations, averaged over all three due date adjustment methods. It can be seen that the previously mentioned objectives reveal approximately 30 % lower *FMA*-rates. Hence, the PCP is capable of entirely synchronizing production under stochastic job arrivals with feed-in management actions in a job shop as well as flow shop production environment if primarily guided by the *ERE*-objective. By doing so, the electricity grid is relieved during peak renewable energy generation periods and the loss of excessive renewable energy generation is counteracted.

However, it must be noted that the higher *FMA*-rates come at the expense of lower job processing rates. While the average job processing rate in the job shop environment with service-oriented objectives (*TA*; *TA, CT*; *TA, CT, ERE*) is at least 98 %, the

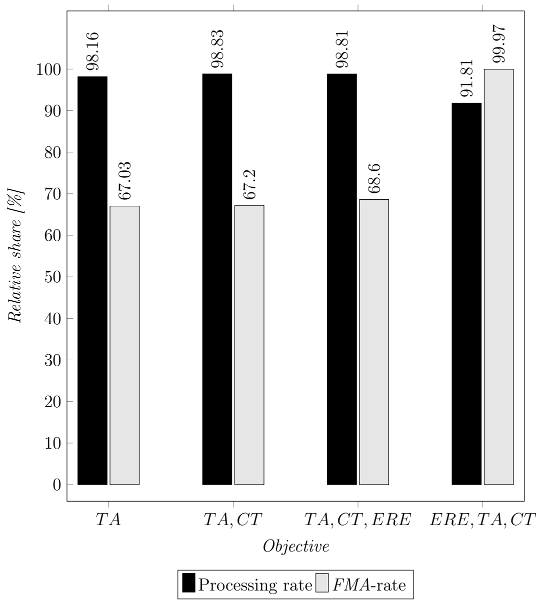

Figure 5.13: Average processing- and *FMA*-rate in job shop production environment.

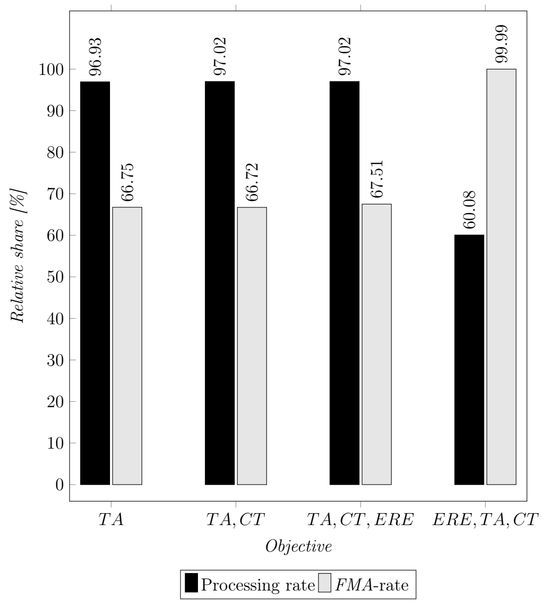

Figure 5.14: Average processing- and *FMA*-rate in flow shop production environment.

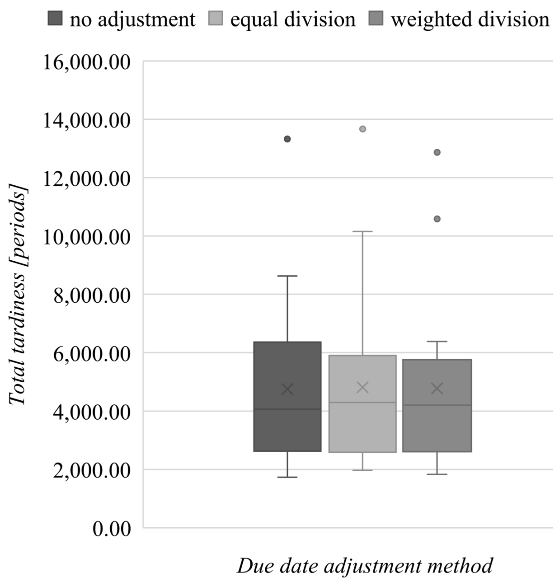

Figure 5.15: Tardiness in job shop production environment with *ERE, TA, CT*-objective.

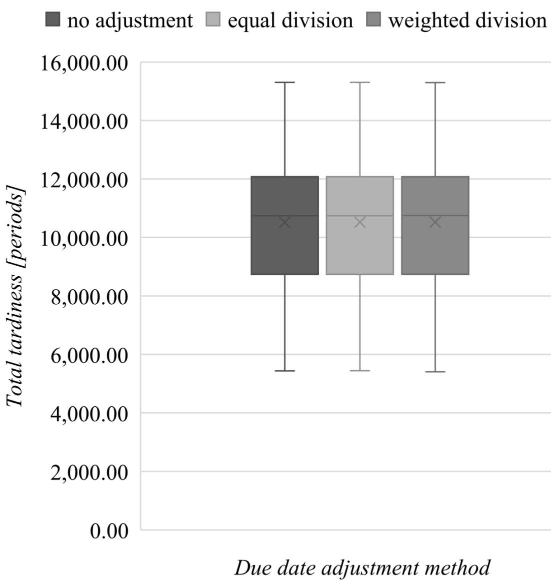

Figure 5.16: Tardiness in flow shop production environment with *ERE, TA, CT*-objective.

energy-oriented objective *ERE, TA, CT* reveals a processing rate of just about 92 %. For the flow shop environment, the processing rate drops drastically to just about 60 %. This drop is because the primary *ERE*-objective lets the PCP put operations into periods with excessive renewable energy no matter how late these periods occur in the simulation horizon. Due to this, subsequently scheduled jobs then cannot be finished within the given time horizon. Next to this, the solutions suffer even more drastically from the primary *ERE*-goal orientation with regard to total tardiness values. These are now orders of magnitude larger than in service-oriented settings. The job shop and flow shop environments reveal total tardiness of nearly $5,000$ and even about $11,000$ periods, respectively, see Figures 5.15 and 5.16. This means that the average tardiness per job is about 36 periods on the 640 time period planning horizon. With each period corresponding to 15 minutes, average job tardiness of 9 hours results here. Resolving this clear conflict among the objectives remains an open issue for future research.

5.6 Conclusion

Peak renewable energy generation poses a risk to electricity grid stability, which is counteracted by feed-in management actions. One opportunity to contribute to grid stabilization without losing renewable energy due to feed-in management actions is to increase the local consumption of electricity. For this, the paper at hand applies event-driven demand response within industrial job shop and flow shop production environments. The optimization model-driven approach handles stochastic job arrivals and combines the scheduling of jobs on machines with charging decisions for support devices on a decentralized decision-making platform. The approach can handle energy-related and service-related objectives in isolation and in combination. By applying the energy-related objective, a company is able to temporarily increase its energy consumption in times of excessive generation of renewable energy and, thus, make feed-in management actions obsolete.

Computational experiments have analyzed the decentral decision-making in a flow shop and a job shop production environment with stochastic job arrival and energy- as well as service-related performance indicators. The computations reveal that low job tardiness can be achieved by combining service-oriented objective functions with machine-specific due date mechanisms. However, a push of energy consumption in periods that face feed-in management actions is hardly possible, if the corresponding energy-related objective is just added as a subordinate objective to a primary tardiness or completion-time objective. Only if this objective is treated as a primary objective, an almost complete synchronization of production activities with feed-in management action periods can be achieved. Such a solution can substantially relieve the electricity grid in times of peak renewable energy generation and foster the consumption of renewable energy that is otherwise lost due to feed-in management. However, such an energy orientation comes along with substantially higher total job tardiness and lower job processing rates, as is shown by the computational results too. Resolving this conflict among the considered objectives clearly requires further research. Furthermore, future research could investigate negotiation mechanisms that support the decision-making platform if limited excessive renewable energy needs to be distributed best possibly among the consuming machines and devices.

Acknowledgments

The authors would like to thank the Gesellschaft für Energie und Klimaschutz Schleswig-Holstein GmbH (EKSH) for promoting this project in form of a PhD scholarship.

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Authors’ Contribution Statements

This chapter describes the authors’ contributions to the essays by using the CRediT taxonomy (Contributor Roles Taxonomy). CRediT is an established taxonomy of in total 14 roles, that can be used to represent each contributor’s specific contribution to the scientific research outputs. Not all of the roles are of significant importance to the essays and only the following roles are used (in alphabetical order): conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, software, supervision, validation, visualization, writing (original draft), and writing (review & editing). The name of the roles is self-explaining and a detailed explanation of them can be found on the CRediT website (https://credit.niso.org/). If the same role applies to multiple authors, CRediT’s suggestion to specify each author’s degree of contribution as ‘lead’, ‘equal’, or ‘supporting’ is followed. The following pages comprise the contribution statements for each distinct author-pairing.

Essay 1

Roles

The research on Essay 1 was a collaborative work from Kristian Bänsch and Thomas Volling (Berlin), Jan Busse and Julia Rieck (Hildesheim), Matthias G. Wichmann (Chemnitz), and Sebastian Scholz and Frank Meisel (Kiel). The authors' contribution to each role is as follows:

Role	Bänsch	Busse	Meisel	Rieck	Scholz	Volling	Wichmann
Conceptualization	equal	equal	equal	equal	equal	equal	equal
Data curation	equal	equal	-	-	equal	-	equal
Formal analysis	equal	equal	-	-	equal	-	equal
Funding acquisition	-	-	equal	-	equal	-	-
Investigation	equal	equal	equal	equal	equal	equal	equal
Methodology	equal	equal	equal	equal	equal	equal	equal
Project administration	lead	-	-	-	-	-	-
Supervision	-	-	equal	equal	-	equal	equal
Validation	equal	equal	equal	equal	equal	equal	equal
Visualization	-	equal	-	-	equal	-	-
Writing (original draft)	equal	equal	equal	equal	equal	equal	equal
Writing (review & editing)	equal	equal	equal	equal	equal	equal	equal

Confirmation

The authors confirm that the above statement of contribution is accurate and true.

14.04.2021
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13.04.2021
Date

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12.04.2021
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Essays 2 and 4

Roles

Sebastian Scholz and Frank Meisel are co-authors of Essays 2 and 4. The same contribution to the roles applies to both essays and is as follows:

Role	Scholz	Meisel
Conceptualization	equal	equal
Data curation	lead	supporting
Formal analysis	lead	supporting
Funding acquisition	equal	equal
Investigation	lead	supporting
Methodology	lead	supporting
Software	lead	-
Supervision	-	lead
Validation	lead	-
Visualization	lead	-
Writing (original draft)	lead	supporting
Writing (review & editing)	lead	supporting

Confirmation

The authors confirm that the above statement of contribution is accurate and true.

27.03.2023 S.Scholz

Date Sebastian Scholz

27.03.2023 Frank Meisel

Date Frank Meisel

Essay 3

Roles

Sebastian Scholz is the single author of Essay 3 and serves as 'lead' in all roles.

Other

Careful proofreading of Essay 3 was done by Frank Meisel. The comments were of great help to improve the manuscript.

Erklärung zum selbstständigen Verfassen der Arbeit

Ich erkläre hiermit, dass ich meine Doktorarbeit „Energy-aware coordination of machine scheduling and support device recharging in production systems" selbstständig und ohne fremde Hilfe angefertigt habe und als Autor bzw. Koautor maßgeblich zu den Fachartikeln beigetragen habe. Alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen der aufgeführten Beiträge, wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

S. Scholz

Kiel, 31.03.2023

Ort, Datum

Unterschrift (Sebastian Scholz)