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

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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

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1 INTRODUCTION

In 2021, Germany emitted a total of 675 million tons of CO_2 [1]. 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 [2]. 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 [3]. More precisely, a loss of 5,818 GWh of renewable energy by feed-in management actions was caused in Germany in the year 2021 [4]. 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 [5].

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 [6], 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 2 reviews the relevant energy-aware literature. Section 3 puts emphasis on the decentral decision-making process under consideration of the availability of renewable energy. Subsequent computational experiments in Section 4 analyze and evaluate the performance of the presented approach. Section 5 concludes the paper.

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. [7]. 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 [8]). 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 [9] 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. [10] 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. [11] 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 [12] provide an overview with a special highlight on studies that consider renewable energy source integration in manufacturing systems, Bänsch et al. [13] study a wide range of relevant energy-aware scheduling publications in depth. The publication by Bänsch et al. [13] 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. [13] 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. [14] 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. [15] 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 [16] 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 [17] 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. [18]. 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 [19] 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 [19] 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.

3 DECENTRAL AGENT-BASED INTRALOGISTICS CHARGING

First, in Subsection 3.1, the underlying manufacturing environment is introduced. Then, Subsection 3.2 introduces the intralogistics charging decision optimization model. Conclusively, Subsection 3.3 presents the algorithm that specifies the considered decentral decision-making and provides explanations for the static charging policy procedures.

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 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, symbolized 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 3.2.

The production environment, depicted in blue in Figure 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,

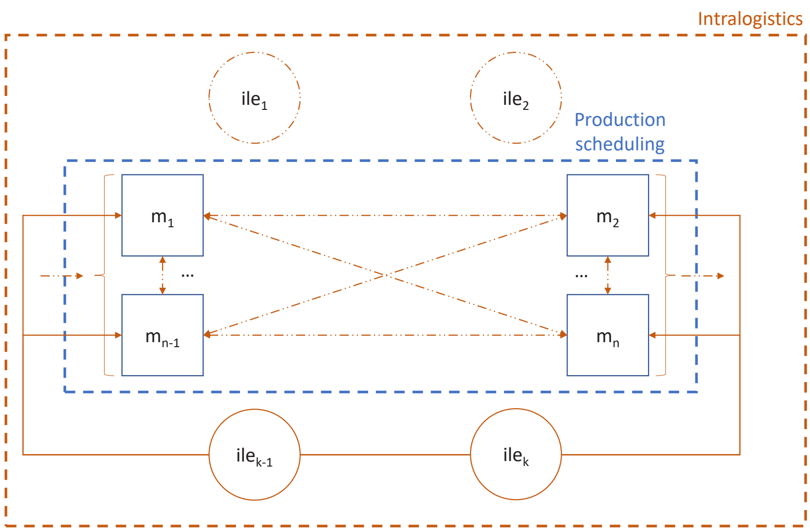

Fig. 1: Schematic manufacturing environment framework.

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 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 [19]. 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 3.2 describes the intralogistics charging decision-making that is triggered through the decentral decision-making procedure. Section 3.3 then represents the decentral decision-making procedure, where individual agents hold the intralogistics and production scheduling decision rules.

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 1 summarizes the notation for this model. The optimization model for the charging decisions of the intralogistics equipment is then as follows.

Table 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]

$$\min \rightarrow \sum_{s \in S} \sum_{t \in T} z_{s,t} \cdot q_s \cdot re_t \tag{1}$$

$$\sum_{s \in S} z_{s,t} \leq 1 \qquad t \in T \tag{2}$$

$$inv_t = inv_{t-1} - de_t + \sum_{s \in S} z_{s,t} \cdot c_s - \left(1 - \sum_{s \in S} z_{s,t}\right) \cdot sdc \qquad t \in T \tag{3}$$

$$\sum_{s \in S} z_{s,t} + \phi_t \leq 1 + scc \qquad t \in T \tag{4}$$

$$0 \leq inv_t \leq inv_{max} \qquad t \in T \tag{5}$$

$$z_{s,t} \in \{0, 1\} \qquad s \in S, t \in T \tag{6}$$

The objective function (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 (2) to (6). Constraints (2) assure that at most one charge mode can be chosen for a period. Constraints (3) 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 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) 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 (5) ensure the non-negativity of intralogistics inventory and respects the maximum capacity. Constraints (6) guarantee the binary character of variables $z_{s,t}$.

3.3 Decentral decision-making procedure

The intralogistics charging optimization model introduced in Section 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 [20], 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 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 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 (1)–(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.

Algorithm 1 Decentral decision-making procedure.

```
E ← M ∪ ILE                                ▷ set of equipment (production machines and intralogistics equipment)
U = [ ]                                    ▷ list of unprocessed jobs
P = [ ]                                    ▷ list of 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 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 ← next request period                 ▷ postpone machine request
            ile.request ← 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 [19]
            e.request ← 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 ∈ ILE do
                if charge policy = s, q OR if charge policy = s, S then
                    if ile.inventory ≤ s then
                        ile.request ← next request period   ▷ define next request
                        q.put(ile)               ▷ insert intralogistics equipment into priority queue
            for j ∈ 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 ≤ e.inv_max then
                e.inventory ← e.inventory + q               ▷ charge with quantity q
        if charge policy = t, S OR if charge policy = s, S then
            Δ = S − e.inventory
            e.inventory ← e.inventory + Δ                   ▷ charge with quantity Δ
        if charge policy = t, q OR if charge policy = t, S then
            e.request ← next request period                 ▷ next request in t periods
        if charge policy = optimization model then
            solve model (1)–(6)                             ▷ solve intralogistics optimization model
            e.inventory ← e.inventory + z_{s,t} · c_s       ▷ charge with quantity z_{s,t} · c_s
            e.request ← next request period   ▷ next request when intralogistics equipment runs idle
    update lp_t
    q.put(e)                                                ▷ put next request in priority queue
```

4 COMPUTATIONAL EXPERIMENTS

In the following, Subsection 4.1 introduces the computational study setup, while Subsection 4.2 describes the charge policy interval parameterization. Based on that, Subsection 4.3 contrasts the static charging policies to the optimization model approach. Subsection 4.4 concludes the computational experiments by considering the impact of different intralogistics demand lengths.

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

Table 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]

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 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 cs of approximately 64 % of the corresponding electricity consumption rate q_s. Besides that, the forklift battery's 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 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.*

4.2 Charge policy interval parameterization

In what follows, we will emphasize the mentioned periodic charging procedures introduced in Section 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 2 and 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

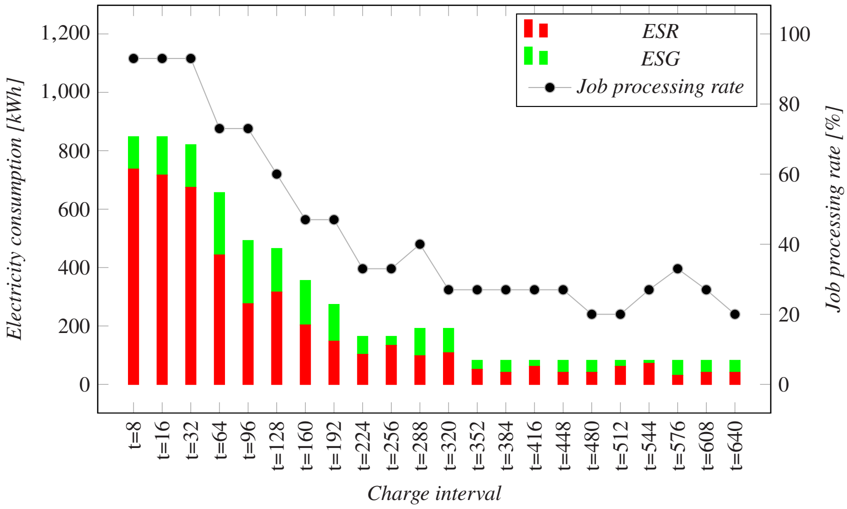

Fig. 2: (t, q)-policy charge interval parameterization.

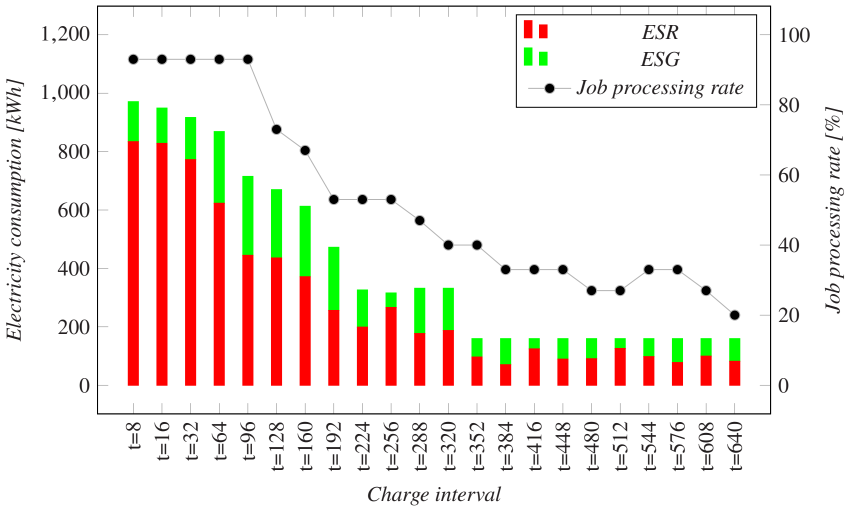

Fig. 3: (t, S)-policy charge interval parameterization.

simulated time horizon, and the intralogistics electricity consumption (left ordinate) for varied values of the charge interval t.

In order to define an appropriate charge interval t for the charge policies (t, q) and (t, S), Figures 2 and 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 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

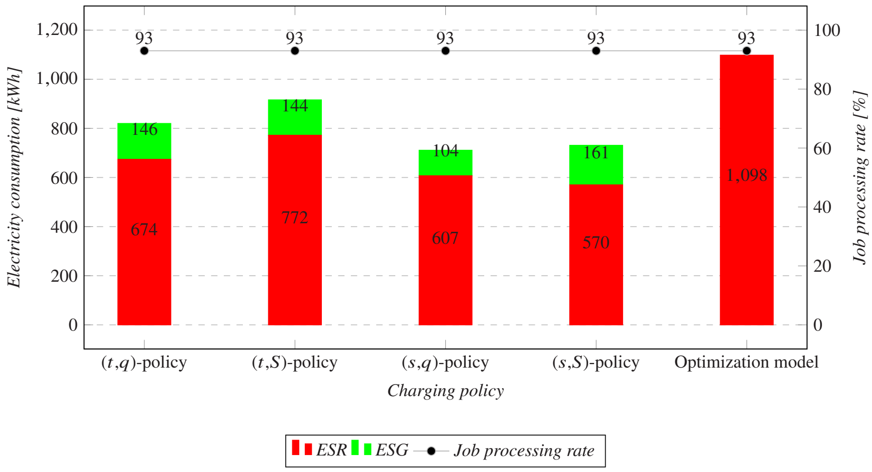

Fig. 4: Comparison of static charge policies and optimization-driven charging.

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.

4.3 Static intralogistics charging policy compared to charging optimization model

In this section, we will emphasize the comparison of the introduced charging policies from Section 4.2 with the intralogistics charging decision optimization model from Section 3.2.

Figure 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-

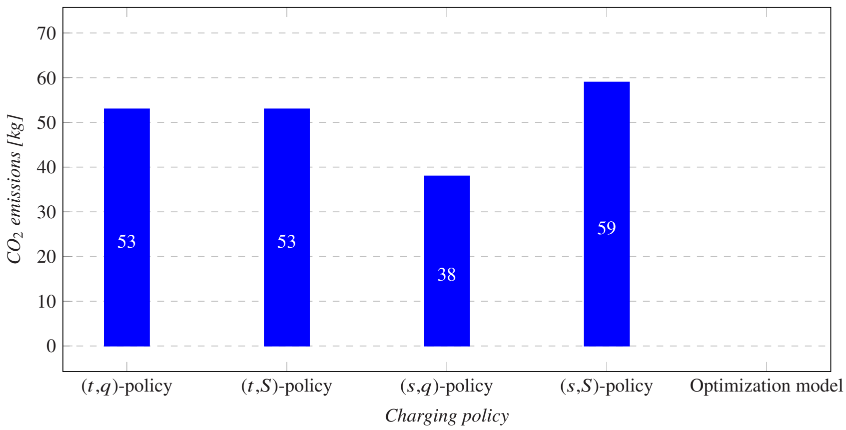

Fig. 5: Charging policy specific CO_2 emissions.

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 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.

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, we quantify the resulting total CO_2 emissions (see Figure 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 [5]. 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 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 3 to 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 3-5) 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 6-8).

Table 3 reports the KPIs for the default demand length of one period, which corresponds to the results depicted in Figure 4 in Section 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 represents the results under a demand length of two periods. With respect to the job processing rate, 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 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 3 to 5 where material handling is executed by the forklift with the highest current inventory level, Tables 6 to 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 3 and 6. Table 7 shows that consistent forklift selection

Table 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	1,098.44
ESG [kWh]	146.13	144.33	103.84	160.88	0.00
Relative ESR usage [%]	82.00	84.00	85.00	78.00	100.00
Job processing rate [%]	93.00	93.00	93.00	93.00	93.00
Machine postponement	0.00	0.00	3.00	4.00	0.00
Compressor delay	0.00	0.00	3.00	4.00	0.00
Forklift delay	0.00	0.00	0.00	0.00	0.00

Table 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]	1,139.31	1,438.94	696.43	697.87	1,812.70
ESG [kWh]	255.72	313.68	124.17	175.28	0.00
Relative ESR usage [%]	82.00	82.00	85.00	80.00	100.00
Job processing rate [%]	73.00	93.00	47.00	47.00	93.00
Machine postponement	183.00	24.00	584.00	463.00	0.00
Compressor delay	183.00	24.00	581.00	368.00	0.00
Forklift delay	0.00	0.00	3.00	95.00	0.00

Table 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]	1,227.86	1,528.02	387.98	867.21	2,234.09
ESG [kWh]	413.37	424.71	49.67	162.14	0.00
Relative ESR usage [%]	75.00	78.00	89.00	84.00	100.00
Job processing rate [%]	53.00	60.00	20.00	33.00	73.00
Machine postponement	421.00	221.00	1,556.00	1,263.00	152.00
Compressor delay	421.00	202.00	1,188.00	723.00	152.00
Forklift delay	0.00	19.00	368.00	540.00	0.00

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. 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 5 and 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 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 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.

Table 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	1,122.24
ESG [kWh]	150.45	144.33	111.04	165.20	0.00
Relative ESR usage [%]	82.00	84.00	85.00	78.00	100.00
Job processing rate [%]	93.00	93.00	93.00	93.00	93.00
Machine postponement	0.00	0.00	3.00	4.00	0.00
Compressor delay	0.00	0.00	3.00	4.00	0.00
Forklift delay	0.00	0.00	0.00	0.00	0.00

Table 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]	1,156.59	1,437.50	715.15	756.91	1,876.63
ESG [kWh]	262.92	313.68	132.81	194.00	0.00
Relative ESR usage [%]	81.00	82.00	84.00	80.00	100.00
Job processing rate [%]	73.00	93.00	47.00	47.00	93.00
Machine postponement	183.00	24.00	602.00	368.00	0.00
Compressor delay	183.00	24.00	602.00	368.00	0.00
Forklift delay	0.00	0.00	0.00	0.00	0.00

Table 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]	1,204.82	1,528.02	406.70	983.83	2,275.24
ESG [kWh]	409.05	420.39	58.31	218.84	0.00
Relative ESR usage [%]	75.00	78.00	87.00	82.00	100.00
Job processing rate [%]	53.00	60.00	20.00	40.00	73.00
Machine postponement	421.00	219.00	1,186.00	901.00	158.00
Compressor delay	421.00	202.00	1,186.00	723.00	158.00
Forklift delay	0.00	17.00	0.00	178.00	0.00

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.

SUMMARY STATEMENT

Conflict of Interest: The authors declare that they have no conflict of interest.

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