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Sustainable Scheduling of Material Handling Activities in Labor-Intensive Warehouses: A Decision and Control Model

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Abstract: In recent years, the continuous increase of greenhouse gas emissions has led many companies to investigate the activities that have the greatest impact on the environment. Recent studies estimate that around 10% of worldwide CO_2 emissions derive from logistical supply chains. The considerable amount of energy required for heating, cooling, and lighting as well as material handling equipment (MHE) in warehouses represents about 20% of the overall logistical costs. The reduction of warehouses' energy consumption would thus lead to a significant benefit from an environmental point of view. In this context, sustainable strategies allowing the minimization of the cost of energy consumption due to MHE represent a new challenge in warehouse management. Consistent with this purpose, a two-step optimization model based on integer programming is developed in this paper to automatically identify an optimal schedule of the material handling activities of electric mobile MHEs (MMHEs) (i.e., forklifts) in labor-intensive warehouses from profit and sustainability perspectives. The resulting scheduling aims at minimizing the total cost, which is the sum of the penalty cost related to the makespan of the material handling activities and the total electricity cost of charging batteries. The approach ensures that jobs are executed in accordance with priority queuing and that the completion time of battery recharging is minimized. Realistic numerical experiments are conducted to evaluate the effects of integrating the scheduling of electric loads into the scheduling of material handling operations. The obtained results show the effectiveness of the model in identifying the optimal battery-charging schedule for a fleet of electric MMHEs from economic and environmental perspectives simultaneously.

Keywords: green warehouse; sustainable scheduling; material handling activity; mobile material handling equipment; warehouse energy management; demand-side management; battery charging; optimization; decision and control

1. Introduction

Recent studies estimate that around 10% of worldwide CO_2 emissions derive from logistical supply chains [1]. Around 11% of the total greenhouse gas (GHG) emissions generated by the logistics sector across the world are caused by warehousing activities [2]. In recent years, an increasing number of companies have been paying more attention to the environmental and economic impacts of warehouse management. In a recent study, Bartolini et al. introduced the term "green warehousing" (GW) to denote a managerial concept integrating and implementing environmentally friendly operations with the objective of minimizing the energy consumption, energy cost, and GHG emissions of a warehouse [3]. The development of GW approaches is also favored by the decreasing costs of smart devices [4], the large availability of distributed sensors [5] and data analytics tools [6], and, in general, advances of information and communication technologies (ICTs) [7]. The results of recent market surveys show that a sustainable approach to warehouse management allows brand fidelity and stakeholder satisfaction to be increased, as well as improving the ability of companies to quickly and flexibly respond to market changes [8]. Consistent with this approach, the introduction of innovative methodologies aimed at maximizing logistical performance and minimizing resource consumption represents a new challenge for scientific research. Indeed, a sustainable approach allows economic, environmental, and social benefits to be brought to logistical supply chains and represents the new key driver for increasing companies' competitiveness. Although many studies have been conducted in the area of green logistics, most of them have focused on transport links, while the increasing use of energy resources due to warehouse management is currently a less explored research theme (Figure 1). However, the reckless use of fossil fuels for transportation has a great impact in terms of logistics' sustainability [9], and the worldwide increase of electrical energy consumption cannot be neglected. According to the International Energy Outlook 2019 [10], in the last ten years, the average worldwide electric energy consumption increased by 16%, while in the industrial sector, an increase of around 25% was observed. In the next thirty years, forecasts predict an increase of electric consumption in the industrial sector of around 47% (Figure 2) [10]. The observed trend highlights a growing need for electric power. Consistent with this consideration, energy-intensive logistical activities require more attention.

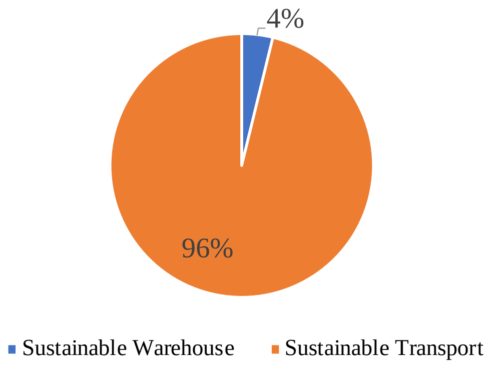

Figure 1. Scopus-indexed papers on sustainable logistics classified in the research topics "Transport" and "Warehouse".

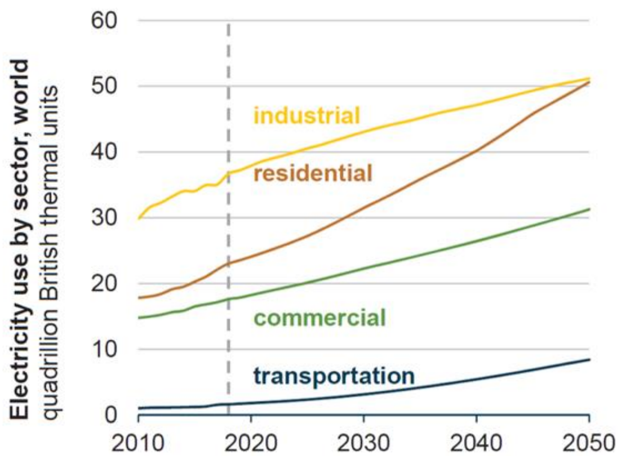

Figure 2. End-use worldwide energy consumption by sector, observed (until 2018) and predicted (until 2050). Source: U.S. Energy Information Administration (EIA) [10].

According to the "European Materials Handling Federation" (https://www.fem-eur.com/), the electricity consumption in logistics chains mostly depends on warehouses' activities, and it is possible to identify two different macro-categories of electrical utilities and consumption:

1. Electric consumption due to direct movements of products or materials both by fixed material handling equipment (FMHE) (such as conveyor systems and automated cranes) and mobile material handling equipment (MMHE) (such as forklift, trucks, etc.);
2. electric consumption due to warehouse facilities like heating, lighting, and air conditioning of the building as well as power supplies of computer systems, office equipment, and miscellaneous equipment such as catering appliances.

It is interesting to note that, according to the data showed in Table 1, a sevenfold increase of the electric consumption due to material handling equipment (MHE) adoption has been observed from 1976 to 2017. On the contrary, in the same period, a reduction of the overall electricity consumption due to warehouse facilities is observed. This trend can be explained considering two conflicting aspects. The first is related to the strong technology development that led to the production of eco-sustainable devices (e.g., Heating, Ventilation and Air Conditioning (HVAC) systems, lighting systems, etc.). The second is related to the increasing number of warehouses in the world.

Table 1. Energy consumption in warehouses by end-use category (1976–2017). Source: https://www.fem-eur.com/.

Time [year]	**Energy consumed [MWh per year]**											
	MHE	**Δ [%]**		**HVAC**	**Δ [%]**		**Lighting**	**Δ [%]**		**Plug Load**	**Δ [%]**	
1976	500			6300			1100			300		
1979	400	−20		2850	−55		2600	+136		200	−33	
1991	800	+100		1400	−51		900	−65		600	+20	
2000	2200	+175		2600	+86		1300	+44		300	−50	
2010	3000	+36		2400	−8		1000	−23		350	+17	
2017	3900	+30	+680	2600	+8	−59	800	−20	−27	600	+71	+100

According to the last report of the World Industrial Truck Statistics, the electric consumption increase due to MHE mainly depends on two aspects:

- Increasing adoption of automated warehouses equipped with electric shuttles, stacker cranes, robots, etc.;
- increasing number of electric forklifts replacing forklifts powered by internal combustion engines thanks to their lower operational and maintenance costs. According to the World Industrial Truck Statistics, the percentage of electric forklifts in the world is over 60% of overall forklifts, and it is very interesting that this trend has grown more than 5% in only five years, from 2014 to 2018 (Figure 3). In the same period, the yearly sales of electric forklifts in Europe have grown by around 40%, and the same trend was observed in other continents (Figure 4).

Consistently with the above issues, the energy consumption related to the increasing adoption of electric MMHEs is a significant aspect of warehouse activities, both from the economic and environmental perspectives. Therefore, the energy management of warehouses plays a fundamental role in identifying strategies for companies to pursue higher performance in terms of productivity, competitiveness, and sustainability at the same time.

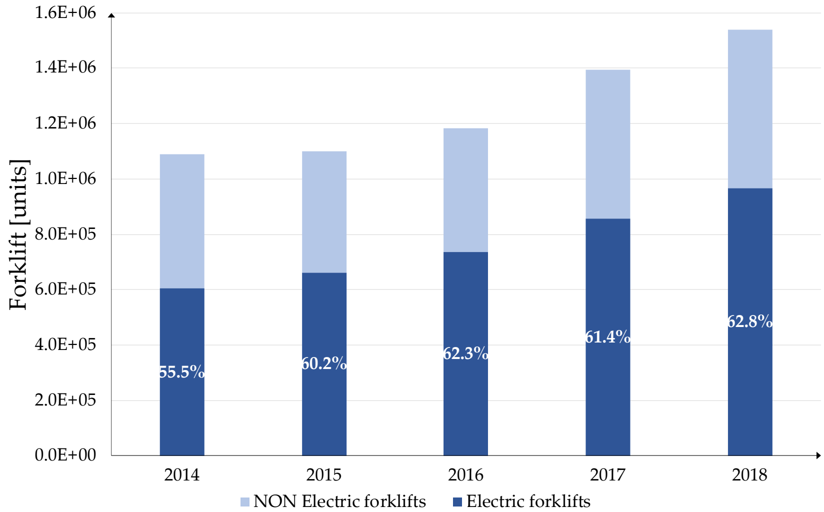

Figure 3. Worldwide electric forklifts units and corresponding market share (2014–2018).

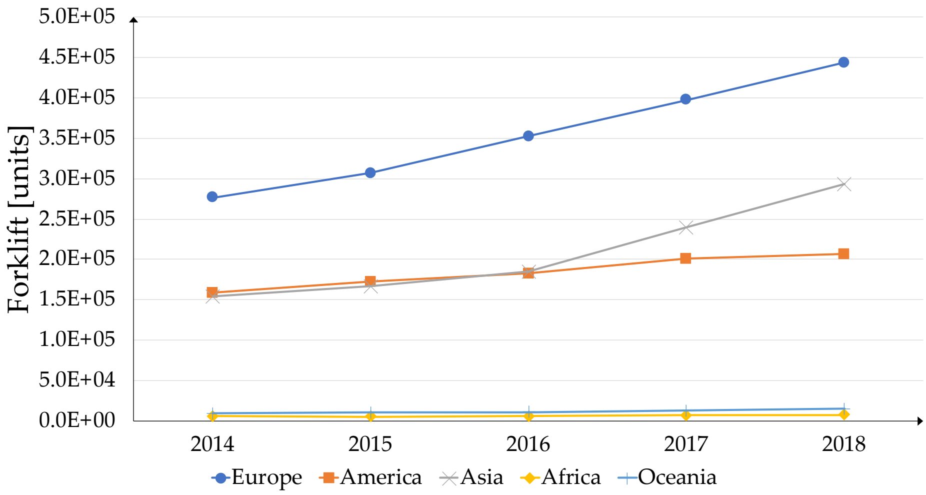

Figure 4. Yearly electric forklift sales per continent (2014–2018).

The active management of electricity demand, commonly known as demand-side management (DSM), has been recognized as an effective approach to provide significant environmental and economic benefits for large electricity consumers such as power-intensive industries and manufacturing companies [11]. Currently, renovation of the electricity market is leading these consumers to pay stratified electricity rates that depend on the time of the day (e.g., peak load, mid-load, and off-peak load). The major purpose of dynamic pricing is to promote the economic efficiency of power systems in order to flatten load curves [12]. In other words, while controlling and influencing the energy demand, dynamic energy pricing leads to reducing the overall peak load and reshaping the demand curve [13]. This implies increasing the grid sustainability, since the overall cost and carbon emission levels are consequently reduced [14].

In this context, this paper addresses the optimal energy schedule for the electric MMHE recharging in warehouses, allowing the reduction of costs while increasing the system sustainability [15]. Consistent with the observations mentioned above, to fully investigate the research problem, the following subsidiary research questions are raised.

- Is it possible to adopt DSM to reduce the economic and environmental impacts of electric MMHE recharging?

- Is there an optimal scheduling strategy allowing the minimization of the cost due to electric MMHE recharging while facing sustainability requirements?

Therefore, the aim of the proposed study is to develop a decision and control model to identify an optimal schedule of material handling activities of a fleet of electric MMHEs (i.e., forklifts) in labor-intensive warehouses from profit and sustainability perspectives. The resulting scheduling approach is based on integer programming (IP) and aims at minimizing the total cost (the sum of the penalty cost related to makespan over all the material handling activities and the total electricity cost for charging batteries of MMHEs), while ensuring that jobs are executed in accordance with priority queuing and that the completion time of battery recharging is minimized. Realistic numerical experiments are conducted to evaluate the effects of the integrated scheduling of electric loads and material handling operations. The obtained results show the effectiveness of the approach in identifying the optimal battery-charging schedule of a fleet of electric MMHEs from economical and sustainable perspectives.

The remainder of the paper is organized as follows: A review of scientific contributions on productivity and sustainability of warehouses is reported in Section 2; in Section 3, the two-step optimization model is detailed; the numerical experiment results are in Section 4; finally, conclusions are in Section 5.

2. Literature Review

According to [16,17], the research on strategies for increasing efficiency of material handling activities in warehouses could be grouped into the following research areas.

(I) Picking strategies: Strategies for pulling store material for orders. In the scientific literature on the energy consumption minimization in material handling processes in warehouses, it is possible to identify two research streams, depending on the picking strategies: "Picker-to-part" and "part-to-picker". Generally, the first one is based on the adoption of FMHEs, exhibiting only steady conveyors, such as belts or sorters, whose energy consumption is merely related to the size (length) of the system. The second one is based on the adoption of MMHEs, considering only mobile equipment, such as forklifts, order picking trucks, and automated storage/retrieval systems (AS/RSs), whose energy consumption is dependent on the equipment specifications and movements [16].

(II) Storage assignment: Strategies for assigning materials to storage locations in warehouses. Bortolini et al. [18] propose a bi-objective model to optimize the scheduling in automatic warehouses. The results highlight the possibility to minimize the energy consumption, ensuring low cycle times. A further approach with the target of reducing the idle time of forklifts is proposed by Ghalehkhondabi and Masel [19]. The authors propose a storage space allocation model that considers the availability of forklifts. An overall optimization model based on constraint programming is developed in [20], allowing the joint application of control policies for storage assignment and sequencing both for time and energy-based optimization. An energy-based storage location assignment, defined as the storage assignment allowing the reduction of energy consumption for warehouse operations, is introduced by Meneghetti and Monti [21]. They revised the storage assignment policies of an automated storage/retrieval system (AS/RS) in order to enhance the flexibility and maximize energy efficiency.

(III) Order Batching: Strategies for sorting orders of a group of customers. The order sequencing issue plays a central role in reducing the energy consumption due to material handling in warehouses. Ene et al. [22] adopt a genetic algorithm to optimize both the routing and batching processes in picker-to-part warehouse systems. The results show that the approach provides efficient solutions to the problem, ensuring significant energy savings. Another interesting investigation that leads to a significant reduction of energy consumption in a warehouse, based on a part-to-picker approach, is developed on systems known as "Kiva" [23]. These processing systems are characterized by mobile robots that hoist racks and bring them directly to stationary pickers. The authors of [23] propose a warehousing energy control model to minimize the energy consumption during machine idling. The model was tested in Brazilian distribution centers considering fleets of forklifts from 5 to 20 units.

(IV) Picker routing: Strategies for identifying the MMHE routing. In [24], a planning process was introduced with the aim of reducing the distance travelled by order pickers. In the same context, a decision-making approach is introduced by Boysen et al. [25], providing an optimized order picking strategy to limit the MMHE fleet size, with significant savings in terms of investment, maintenance, and energy charging equipment. Zulj et al. [17] proposed a model allowing the identification of a picking–routing strategy based on stacking constraints. The effects of the human behavior on the efficiency of routing policies in order picking are investigated in [26]. The study is focused on how deviations from routes impact the efficiency of different routing policies. To quantify the effects of route deviations and evaluate the performance of routing policies, an agent-based simulation model is developed.

(V) Warehouse layout: Strategies for designing the most efficient layout in terms of handled materials. Starting from the observation that about 50% of total order-picking time is spent on travelling, in [27], a study on the routing of forklifts in warehouses with different layouts is proposed. The research highlighted that the choice of the proper layout is strongly related to the adopted picking technology. An occasional charging station location model was developed in [28] to maximize recharging breaktimes for non-road electric vehicles (i.e., forklifts and other MMHEs).

In this paper, we focus on the first class of strategies, with particular regard to mobile equipment.

Considering the three pillars of sustainability (i.e., economic, social, and environmental), the literature on GW strategies can be classified in three different areas: Green warehouse management, environmental impact of warehouse building, and energy saving in warehousing [3]. The first area includes warehouse policies, which affect the warehouse performance under an environmental perspective (e.g., standard implementation, storage strategies, supply policies, etc.); the second area focuses on key warehouse characteristics that contribute to reducing environmental emissions and energy consumption (e.g., warehouse size, space utilization, lighting, etc.); the last area is related to the increase of the energy efficiency in the warehouse by means of the reduction of the energy required for material handling activities. The proposed study belongs to this last research area.

In the class of GW management contributions, we recall the work by Akandere [29], which is focused on minimizing the stock level, optimizing the supply policies, and decreasing waste. A study investigating how the inventory process enhances the sustainability of food companies is proposed by Petljak et al. [30], providing a guide supporting managers for implementing new practices to improve warehouse performance from the environmental perspective. The relationship between GW practices and factors affecting them in Malaysian companies is studied in [31].

In the area of the environmental impact due to warehouse building, the energy performance in warehouses is mainly affected by the general building characteristics that determine the consumption due to lighting or HVAC systems [32–34]. Concerning the annual heating demand, three alternatives for reducing electrical energy consumption and peak demand based on rooftop solar panels, battery energy storage, and HVAC set point adjustments are compared in [35]. A method of obtaining energy savings by adjusting HVAC set points based on occupant comfort, measured using the predicted mean vote and occupancy information, is proposed by Ardiyanto et al. [36].

Concerning the third research area, most studies on the reduction of energy consumption due to warehousing activities are based on the adoption of energy-saving material handling systems. Minav et al. [37] prove that the recovery of energy from the hydraulic system of a forklift, adopting an industrial electric drive and an electrical servo motor, is possible, with an increase of efficiency of around 20% compared with traditional systems. A potential energy recovery system is also introduced in an electro-hydraulic industrial forklift in [38].

Despite the increasing attention of the scientific literature toward energy issues in GW management and electric demand of warehouse building facilities, a lack of studies on energy consumption due to material handling activities is highlighted in [39]. In addition, there are very few studies in which the charging schedule of MMHEs is optimized from the economic and environmental perspectives. In particular, authors in [40,41] introduced an electric vehicle routing problem with time windows and recharging stations; the proposed model provides the cost-optimal routes for electric commercial vehicles, considering a limited battery capacity and the possibility to identify a route where recharging stations are available. However, we first note that the underlying assumption is that recharging stations are always available when vehicles are plugged in (i.e., the scheduling of charging stations is neglected). Second, the energy cost due to the electric vehicles' recharging process is not addressed (i.e., the energy pricing is not dynamic). Instead, the uncoordinated random charging of electric vehicles brings a variety of challenges to the power quality and reliability of power grids. For example, if a large number of electric vehicles start charging at the same time, a peak demand may be originated in the power grid, resulting in the need for additional power generation capacity and electricity infrastructure. Summing up, although these studies represent a good reference for the management of recharging stations, they do not consider realistic constraints in terms of recharging time and lifetime regarding the non-road vehicles generally adopted for warehousing activities.

From the analysis of the scientific literature, it is thus evident that no studies focus on the integration of electric MMHE activity scheduling and the optimal management of their charging stations. In this context, the application of intelligent DSM to industrial electric equipment is rapidly gaining momentum in the scientific research and industry [11]. Similarly to the residential DSM, where energy users schedule their domestic activities in accordance with demand response mechanisms [42], load scheduling has recently attracted significant attention in the industrial sector. Since the emerging paradigm of the smart grid requires companies to pay dynamic time-varying electricity costs, it is profitable for such consumers to reschedule and shift the energy demand to low-rate periods [43]. On the other hand, industrial DSM strongly integrates operation scheduling and energy management, which requires detailed knowledge of processes as well as clear modeling of the power market.

Summing up, to the best of the authors' knowledge, no studies propose decision-making approaches to jointly determine the activities and optimal charging schedules of electrically powered forklifts for material handling activities in labor-intensive warehouses. In order to overcome the highlighted gap, in the next section, we define an optimization model for identifying an optimal schedule of material handling activities of a fleet of electric forklifts in a labor-intensive warehouse under profit and sustainability perspectives.

3. System Modeling and Problem Formulation

The proposed optimization problem is formulated as follows.

3.1. Problem Statement

The proposed decision-making technique aims at minimizing the total cost of electrical handling activities, which is the sum of the penalty cost related to makespan over all of the material handling activities and the electricity cost for charging batteries of MMHEs, while ensuring that jobs are executed in accordance with priority queuing and that the completion time of the overall battery recharging process is minimized. Hence, the problem statement may be described as follows. Given a set of jobs characterized by priorities and durations, a set of forklifts and a set of charging stations with corresponding initial states, and a set of conflicting criteria (namely, the penalty cost related to job ordering, penalty cost related to makespan, penalty cost related to overall completion times of battery recharging processes, and energy cost for the overall charging of forklift batteries over the planning horizon) with corresponding weighting factors, the overall optimal scheduling of the material handling activities must be determined, including: The optimal scheduling of each job (i.e., job starting/ending times and forklift assignment), the optimal strategies of battery replacement (i.e., when forklifts have to replace empty batteries with fully charged ones), and the optimal energy scheduling of charging stations (i.e., energy profile required by charging stations to charge batteries over time).

3.2. Assumptions

The following assumptions are made:

1. Each job is composed by an uninterruptible and ordered sequence of picking operations.
2. Jobs are executed in accordance with a priority queuing. This is one of the dispatching rules that is commonly used in in the material handling scheduling [44].
3. Each forklift can process only one job at a time. The related processing time is known and independent from forklift and job execution order. This is a classical assumption made in the material handling scheduling [44].
4. The processing time of each job is less than the fully charged battery capacity. This assumption can be removed by allowing the replacement of batteries within the execution of activities that require a long time.
5. Battery usage on each forklift is zero during idling times. This assumption is motivated by the fact the battery leakage constant time is much larger than idling times between consecutive activities [45].
6. All jobs are completed within the considered planning horizon. This assumption is straightforwardly verified by suitably setting the value of the planning horizon.
7. There are no overlapping constraints between forklifts performing different jobs. This assumption is obviously derived by the independence of activities.
8. Change of battery is done in a neglectable time on any forklift. This assumption can be removed by introducing the battery replacement as an activity with non-zero duration.
9. Battery charging is an interruptible load and is performed with a fixed energy rate, i.e., we assume a linear recharge of vehicle batteries as in [13].
10. The pricing of energy bought from the power grid is variable during the planning window but known ahead of time. This is a classical assumption in the field of DSM [14].

3.3. Indices and Sets

The following notation is used:

$\mathcal{B}$	set of levels of battery capacity
i	index of places in job sequences ($i \in \mathcal{J}$)
$\mathcal{J}$	set of places in the job sequence addressed by forklifts $\{1, \ldots, i, \ldots, K\}$
k	identifier of jobs ($k \in \mathcal{K}$)
$\mathcal{K}$	set of jobs $\{1, \ldots, k, \ldots, K\}$
m	identifier of forklifts ($m \in \mathcal{M}$)
$\mathcal{M}$	set of forklifts $\{1, \ldots, m, \ldots, M\}$
n	identifier of battery charging stations ($n \in \mathcal{N}$)
$\mathcal{N}$	set of charging stations $\{1, \ldots, n, \ldots, N\}$
t	index of time slots ($t \in \mathcal{T}$)
$\mathcal{T}$	planning horizon $\{1, \ldots, t, \ldots\ T\}$.

3.4. Parameters

The following parameters are used:

a_{nt}	1 if charging station n is available at time t; 0 otherwise
b_{min}	minimum battery capacity
b_{max}	fully charged battery capacity
b_0^m	capacity of the battery in forklift m at the beginning of the planning horizon
b_f^m	capacity of the battery on forklift m at the end of final setup
c_0^m	setup completion time of forklift m
e_t	energy unitary cost at time slot t
K	number of jobs
l_k	processing duration of job k
L	a large number
M	number of electric forklift

N	number of charging stations
p_k	processing priority of job k
q_m	penalty unitary cost related to the job makespan
q_p	penalty unitary cost related to the job ordering
q_r	penalty unitary cost related to the battery recharging completion time
T	number of time slots
ϵ	amount of energy required to charge one battery in one time slot
μ^I	weighting factor of the makespan penalty term in the objective function of the first-step optimization
μ^{II}	weighting factor of the job ordering penalty term in the objective function of the first-step optimization
π^I	weighting factor of the makespan penalty term in the objective function of the second-step optimization
π^{II}	weighting factor of the recharging completion time penalty term in the objective function of the second-step optimization
π^{III}	weighting factor of the energy cost term in the objective function of the second-step optimization.

3.5. Decision Variables

The following decision variables are used:

b_i^m	capacity of battery on forklift $m \in \mathcal{M}$ at the beginning of activity $i \in [1, I_m + 1]$ taking into account the potential battery replacement
c_{max}	maximum completion time over all the jobs (makespan)
$c_{max,id}$	maximum completion time over all the jobs and forklifts (makespan), assuming that battery capacity is infinite
c_i^m	completion time of job $i \in [1, I_m]$ on forklift $m \in \mathcal{M}$
$c_{max,id}^m$	maximum completion time of forklift $m \in \mathcal{M}$, assuming that battery capacity is infinite
d_i^m	idling time before processing job $i \in [1, I_m]$ on forklift $m \in \mathcal{M}$
EC	energy cost for the overall charging of forklift batteries over the planning horizon
E_t	energy for charging batteries of forklifts at time slot t
I_m	number of jobs allocated to forklift m
j_i^m	identifier of the i-th activity—including jobs ($j_i^m \in \mathcal{K}$), forklift initial setup ($j_i^m = 0$), and final setup ($j_i^m = I_m + 1$)—related to the m-th forklift
MC	penalty cost related to makespan
PC	penalty cost related to job ordering
RC	penalty cost related to overall completion times of battery recharging processes
r_i^m	completion time of recharging process related to the battery replaced at the beginning of activity $i \in [1, I_m + 1]$ on forklift $m \in \mathcal{M}$
r_{max}^n	overall completion time of recharging processes related to charging station $n \in \mathcal{N}$
s_i^m	starting time of activity $i \in [1, I_m + 1]$ on forklift $m \in \mathcal{M}$
x_{ik}^m	1 if job k is the i-th activity executed by forklift m; 0 otherwise
z_i^{mn}	1 if forklift $m \in \mathcal{M}$ replaces its battery with a fully-charged one at the beginning of activity $i \in [1, I_m + 1]$ at charging station $n \in \mathcal{N}$; 0 otherwise
β_i^m	capacity of battery on forklift $m \in \mathcal{M}$ at the beginning of activity $i \in [1, I_m + 1]$
γ_i^{mt}	1 if t is the completion time of the recharging window for the battery replaced at the beginning of activity $i \in [1, I_m + 1]$ on forklift $m \in \mathcal{M}$; 0 otherwise
δ_i^{mt}	1 if t is within the recharging window for the battery replaced at the beginning of activity $i \in [1, I_m + 1]$ on forklift $m \in \mathcal{M}$; 0 otherwise
ρ_i^{mt}	1 if the battery replaced at the beginning of activity $i \in [1, I_m + 1]$ is actually recharged in time slot t on forklift $m \in \mathcal{M}$; 0 otherwise
σ_i^{mt}	1 if t is the starting time of the recharging window for the battery replaced at the beginning of activity $i \in [1, I_m + 1]$ on forklift $m \in \mathcal{M}$; 0 otherwise.

3.6. Optimization Model

The scheduling problem under investigation is well known to be characterized by a high complexity. As indicated by the related literature in the area of material handling scheduling, exact optimization methods are able to address a limited number of jobs and study simple scenarios with simplifying assumptions, due to the high computational time required even in small-size problems [44]. Conversely, the performance of approximated methods is superior to that of exact ones, since the former allows addressing larger-size scenarios and integrating complimentary aspects within a reasonable solving time [44]. Consequently, heuristic methods are the most adopted solution approaches in the area of material handling scheduling.

Following this trend, we define a two-step optimization model: The proposed approach sequentially applies two optimization steps. A scheme of the overall decision process is illustrated in Figure 5. The first optimization aims at determining a high-level scheduling of jobs to be executed by forklifts. In particular, this step performs both the ordering of jobs in accordance with the given job priorities and the assignment to forklifts, ensuring an equal distribution of jobs between forklifts. At this step, the need of battery replacement is neglected and, thus, no detail about state of charge of forklift batteries is considered. The results of this optimization step are used by the second optimization problem, which conversely aims at determining the detailed scheduling of jobs and the optimal forklift charging strategies. In particular, this step is focused on the energy management of battery recharging, ensuring that the resulting scheduling of jobs minimizes the overall makespan. For both steps, a detailed formulation of the optimization problem is reported in the sequel, including description of involved decision variables, objective function, and constraints.

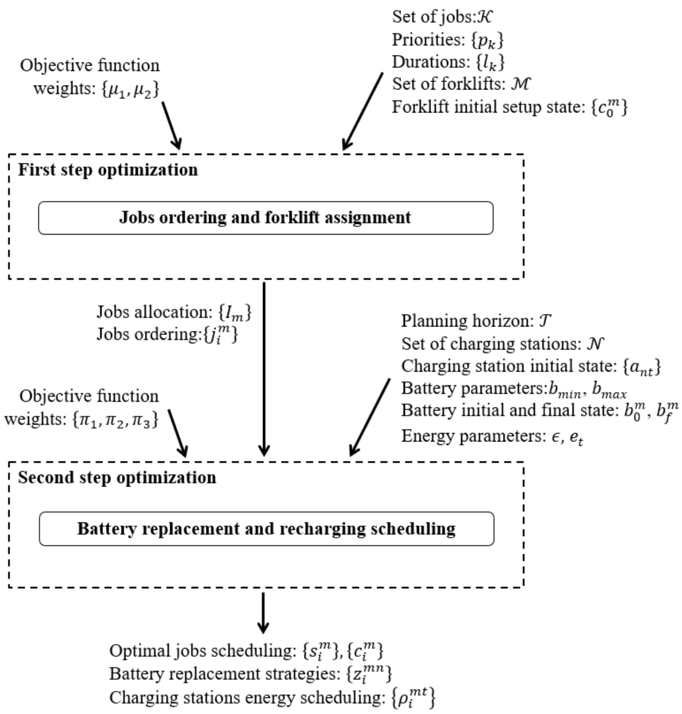

Figure 5. The two-step optimization approach.

3.6.1. First-Step Optimization

As for the first-step optimization, the mathematical model is defined as follows:

$$\min\left(\mu^I MC + \mu^{II} PC\right) \quad (1)$$
s.t.

$$\sum_{i \in \mathcal{J}} \sum_{m \in \mathcal{M}} x_{ik}^{m} = 1, \forall k \in \mathcal{K} \tag{2}$$

$$\sum_{k \in \mathcal{K}} x_{ik}^{m} \leq 1, \forall i \in \mathcal{J}, \forall m \in \mathcal{M} \tag{3}$$

$$c_{max,id}^{m} = c_{0}^{m} + \sum_{i \in \mathcal{J}} \sum_{k \in \mathcal{K}} x_{ik}^{m} l_i, \ \forall m \in \mathcal{M} \tag{4}$$

$$c_{max,id} \geq c_{max,id}^{m}, \ \forall m \in \mathcal{M} \tag{5}$$

$$MC = q_m c_{max,id} \tag{6}$$

$$PC = q_p \sum_{m \in \mathcal{M}} \sum_{i \in \mathcal{J}} i \sum_{k \in \mathcal{K}} x_{ik}^{m} p_k \tag{7}$$

$$x_{ik}^{m} \in \{0, 1\}, \ \forall k \in \mathcal{K}, \forall i \in \mathcal{J}, \ \forall m \in \mathcal{M} \tag{8}$$

$$c_{max,id}^{m} \in \mathcal{T}, \forall m \in \mathcal{M}, \ c_{max,id} \in \mathcal{T}. \tag{9}$$

The objective in (1) is minimizing the makespan while ensuring that jobs are executed in accordance with priority queuing. The first contribution in (1)—weighted by μ^{I}—represents the penalty cost related to the ideal makespan, i.e., the completion time of all of the jobs assuming that all of the forklifts have an infinite battery capacity (i.e., no need for battery replacement). The second term in (1)—weighted by μ^{II}—characterizes the allocation of jobs among different forklifts in accordance with a higher priority—first completed rule. Constraints (2) and (3) regulate how jobs can be distributed between all of the forklifts, whilst (4)–(7) are related to the job ordering and forklift assignment. Finally, Constraints (8) and (9) specify the integrality conditions on the defined decision variables. The meaning of each constraint is detailed as follows.

Preliminarily note that a sequence (represented by the index $i \in \mathcal{J}$) with K places is assigned to each forklift. Such a sequence will be partially occupied by the jobs that are actually executed by the given forklifts: Only the first $I_m \leq K$ places will be filled by each forklift $m \in \mathcal{M}$, whilst the last one will be kept unassigned. Note that the inequality $I_m \leq K$ holds, since the K jobs will be, in general, distributed between all the forklifts ($M \geq 1$). Coherently, Constraint (2) makes sure that each job is assigned to one sequence place of one forklift only, and Constraint (3) ensures that each sequence place of each forklift is assigned to no more than one job. Constraint (4) determines the ideal completion time of forklifts, taking the initial setup time into account and assuming an infinite battery capacity. Constraint (5) ensures that the ideal completion time of each forklift is lower than or equal to the ideal makespan. Constraint (6) calculates the total penalty cost related to the completion time over all of the jobs. Constraint (7) calculates the total penalty cost related to the job ordering.

Summing up, the first-step optimization problem (1)–(9) results in a linear integer program aimed at determining the $M+1$ integer and K^2M binary variables, which minimize the objective function in (1) and meet the $2(M+1)$ bounding constraints, $(K+M)$ equality constraints, and the $M(K+1)$ inequality constraints. The resolution of (1)–(9) allows the determination of $(j_1^m, \ldots, j_i^m, \ldots, j_{I_m}^m)$ ($\forall m \in \mathcal{M}$), i.e., the ordered sequence of I_m jobs assigned to each forklift m:

$$j_i^m = k \ \Leftrightarrow \ x_{ik}^{m} = 1, \forall m \in \mathcal{M}, \forall i \in [1, I_m], \tag{10}$$

where the number I_m of jobs allocated to forklift m is computed by:

$$I_m = \sum_{i \in \mathcal{J}} \sum_{k \in \mathcal{K}} x_{ik}^{m}, \forall m \in \mathcal{M}. \tag{11}$$

3.6.2. Second-Step Optimization

As for the second-step optimization, the mathematical model is defined as follows:

$$\min\left(\pi^{I}MC + \pi^{II}RC + \pi^{III}EC\right) \quad \text{s.t.} \tag{12}$$

$$c_i^m \geq s_i^m + p_{j_i^m}, \forall m \in \mathcal{M}, \forall i \in [1, I_m] \tag{13}$$

$$s_{i+1}^m \geq d_{i+1}^m + c_i^m, \forall m \in \mathcal{M}, \forall i \in [0, I_m] \tag{14}$$

$$c_{max} \geq c_{I_m}^m,\ \forall m \in \mathcal{M} \tag{15}$$

$$MC = q_m c_{max} \tag{16}$$

$$\beta_1^m = b_0^m, \forall m \in \mathcal{M} \tag{17}$$

$$\beta_{i+1}^m = \left(b_i^m - l_{j_i^m}\right), \forall m \in \mathcal{M}, \forall i \in [1, I_m] \tag{18}$$

$$b_i^m = \left(1 - \sum_{n \in \mathcal{N}} z_i^{mn}\right)\beta_i^m + \sum_{n \in \mathcal{N}} z_i^{mn} b_{max},\ \forall i \in [1, I_m + 1] \tag{19}$$

$$b_i^m \geq \left(l_{j_i^m} + b_{min}\right), \forall m \in \mathcal{M}, \forall i \in [1, I_m] \tag{20}$$

$$b_{I_m+1}^m \geq b_f, \forall m \in \mathcal{M} \tag{21}$$

$$\sum_{n \in \mathcal{N}} z_i^{mn} \leq 1,\ \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{22}$$

$$\sum_{t \in \mathcal{T}} \sigma_i^{mt} t = s_i^m \sum_{n \in \mathcal{N}} z_i^{mn},\ \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{23}$$

$$\sum_{t \in \mathcal{T}} \gamma_i^{mt} t = r_i^m \sum_{n \in \mathcal{N}} z_i^{mn},\ \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{24}$$

$$r_{max}^n \geq r_i^m z_i^{mn},\ n \in \mathcal{N}, \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{25}$$

$$RC = q_r \sum_{n \in \mathcal{N}} r_{max}^n \tag{26}$$

$$\sum_{t \in \mathcal{T}} \gamma_i^{mt} t \geq \sum_{t \in \mathcal{T}} \sigma_i^{mt} t,\ \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{27}$$

$$\sum_{t \in \mathcal{T}} \sigma_i^{mt} + \sum_{t \in \mathcal{T}} \gamma_i^{mt} \leq L \sum_{n \in \mathcal{N}} z_i^{mn},\ \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{28}$$

$$\sum_{t \in \mathcal{T}} \sigma_i^{mt} \leq 1, \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{29}$$

$$\sum_{t \in \mathcal{T}} \gamma_i^{mt} \leq 1, \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{30}$$

$$\delta_i^{mt} = \sum_{\tau=1}^{t} \left(\sigma_i^{m\tau} - \gamma_i^{m\tau}\right), \forall t \in \mathcal{T}, \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{31}$$

$$\rho_i^{mt} \leq \delta_i^{mt},\ \forall t \in \mathcal{T}, \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{32}$$

$$\sum_{t \in \mathcal{T}} \rho_i^{mt} = \left(b_{max} - \beta_i^m\right) \sum_{n \in \mathcal{N}} z_i^{mn}, \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{33}$$

$$a_{nt} - \sum_{m \in \mathcal{M}} \sum_{i \in [1, I_m+1]} \delta_i^{mt} z_i^{mn} \geq 0, \forall n \in \mathcal{N}, \forall t \in \mathcal{T} \tag{34}$$

$$E_t = \epsilon \sum_{j \in \mathcal{J}} \sum_{m \in \mathcal{M}} \rho_i^{mt} \tag{35}$$

$$EC = \sum_{t \in \mathcal{T}} e_t E_t \tag{36}$$

$$s_i^m, c_i^m, d_i^m \in \mathcal{T}, \forall m \in \mathcal{M}, \forall i \in [1, I_m] \tag{37}$$

$$z_i^{mn} \in \{0, 1\}, \ \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \forall i \in [1, I_m] \tag{38}$$

$$\beta_i^m, b_i^m \in \mathcal{B}, \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1] \tag{39}$$

$$\sigma_i^{mt}, \gamma_i^{mt}, \delta_i^{mt}, \rho_i^{mt} \in \{0, 1\}, \ \forall m \in \mathcal{M}, \forall i \in [1, I_m + 1], \ \forall t \in \mathcal{T}. \tag{40}$$

The objective in (12) is minimizing the total cost, which is the sum of the penalty cost related to makespan over all of the jobs (weighted by π^I), the penalty cost related to the completion time of the overall battery recharging process (weighted by π^{II}), and the total electricity cost for charging batteries of forklifts (weighted by π^{III}). Constraints (13)–(16) are related to the job scheduling, whilst (17)–(26) and (27)–(36) are aimed at scheduling the optimal battery changes and determining the optimal recharging cost strategies, respectively. Finally, Constraints (37)–(40) specify the integrality conditions on the defined decision variables. The meaning of each constraint is detailed as follows.

Constraint (13) guarantees that, for each job, the difference between the starting and the completion times is equal to the processing time. Constraint (14) ensures that each activity $i + 1$ is initiated later than the completion of its immediately preceding activity i on any forklift. Note that activity $i = 0$ identifies the initial setup of any forklift occurring at the beginning of the planning horizon, whilst activity $i = I_m + 1$ identifies the final setup of any forklift occurring at the end of operations. Constraint (15) ensures that the completion time of each job is lower than or equal to the makespan. Constraint (16) calculates the total penalty cost related to the completion time over all of the jobs.

Constraints (17) and (18) update the battery capacity through the execution of activities. In particular, (17) initializes the battery capacity in forklifts in the jobs allocated at the beginning of the planning horizon, whilst (18) calculates the residual battery capacity by first-order state transition between subsequent activities. Constraint (19) updates the residual battery capacity at the beginning of activity i, taking into account the eventual replacement with a fully charged battery. Constraint (20) guarantees that the capacity of the battery in any forklift is enough to complete job i, whilst (21) guarantees that the capacity of the battery in any forklift at the end of the final setup is not lower than the required final state. Constraint (22) makes sure that battery replacement in any activity is assigned to one charging station only. Constraints (23) and (24) determine the starting and completion times of the battery charging processes, respectively. Constraint (25) determines the completion time of any charging station. Constraint (26) calculates the total penalty cost related to the completion time over all of the jobs and all of the charging stations.

Constraint (27) ensures that the completion of any battery charging process for each activity $i + 1$ occurs no earlier than the corresponding starting time. Constraint (28) forces the starting and completion times of the battery charging process related to job j to zero in the case that job j is not assigned to a battery replacement. Constraints (29) and (30) ensure the unicity of starting and completion instants for each battery charging process in the whole planning window. Constraint (31) calculates the time window when the charging could be executed. Constraints (32) and (33) determine the time slots when the energy is bought from the grid and used to charge the battery. Constraint (34) ensures that the number of available fully charged batteries is non-negative in each time slot. Constraint (35) calculates the energy consumed in each time slot. Constraint (36) calculates the total energy cost related to the full battery charging over the whole time horizon.

Finally, comparing the approach with the related literature, we remark that, to the best of the authors' knowledge, the available contributions on scheduling of MMHE activities do not treat the optimal energy charging under dynamic energy pricing. We finally remark that the case of a logistics optimization model dealing with recharging stations for electric vehicles is addressed only by Schneider et al. [40], where the focus is anyway on the field of outbound logistics. Differently from [40], our work focuses on the inbound logistics and, in particular, on warehousing. Specifically, the novel contribution of our work lies in integrating the scheduling of electric loads into the scheduling of MMHE operations. To this aim, we deal with a time-dependent energy pricing (that allows the minimization the cost of energy consumption) and we consider the operation management of charging stations (this allows us to effectively acquire energy during low-cost time slots, resulting in a smart and energy-cost-saving-oriented scheduling).

Summing up, the second-step optimization problem (12)–(40) is a non-linear integer program, since cross-product terms $z_i^{mn}\beta_i^m$, $s_i^m z_i^{mn}$, $r_i^m z_i^{mn}$, and $\delta_i^{mt} z_i^{mn}$ are present in (19) and (33), (23), (24) and (25), and (34), respectively. The resolution of (12)–(40) allows the determination of the optimal job scheduling $\{s_i^m\}$, $\{c_i^m\}$, the battery replacement strategies $\{z_i^{mn}\}$, and the charging station energy scheduling $\{\rho_i^{mt}\}$. Following the approach proposed by [46], a linearized version of (12)–(40) can be obtained. The resulting linear integer programming problem consists of determining the $(8M(J+1)+JM+2)$ integer and $M(J+1)(1+4T)$ binary variables, which minimize the objective function in (12) and meet the $2(8M(J+1)+JM+2)$ bounding constraints, $(MT(J+1)+4M(J+1)+2JM+2M)$ equality constraints, and the $(MT(J+1)+14M(J+1)+2JM+2M+T)$ inequality constraints.

4. Numerical Experiments

In this section, we report the results of various realistic numerical experiments conducted in different scenarios of analysis to demonstrate the profit and sustainability of our proposed approach. Since the main goal of this work is to propose a novel scheduling of material handling activities in labor-intensive warehouses from a proof-of-concept perspective, the conducted numerical experiments aim at showing the potentiality of the proposed optimization strategy in terms of effectiveness and efficiency in reducing the total makespan and energy cost under several scenarios. Indeed, we investigate the effects of various factors (i.e., varying the number of jobs, the number of forklifts, and the number of charging stations) in the scheduling of material handling activities.

4.1. Setup of Experiments

We consider a warehouse where M electric forklifts have to handle K independent jobs while recharging their own batteries using N charging stations. The planning horizon is composed by $T = 60$ time slots. We address the following three scenarios of analysis:

1. Scenario I: We analyze in detail the optimal job scheduling, battery replacement strategies, and charging station energy scheduling when $K = 15$ jobs are handled using $M = 2$ forklifts and $N = 3$ charging stations under two different model set-ups:
   - Case I.a: With energy scheduling, i.e., $\mu^I = \mu^{II}$ =1/2 and $\pi^I = \pi^{II} = \pi^{III}$ =1/3;
   - Case I.b: Without energy scheduling, i.e., $\mu^I = 1$, $\mu^{II} = 0$ and $\pi^I = 1$, $\pi^{II} = \pi^{III}$ =0.
2. Scenario II: We compare the optimal job scheduling, battery replacement strategies, and charging station energy scheduling obtained in scenario I.a (i.e., $K = 15$ jobs, $M = 2$ forklifts and $N = 3$ charging stations) with the results obtained under two different configurations:
   - Case II.a: $M = 3$ forklifts and $N = 3$ charging stations;
   - Case II.b: $M = 3$ forklifts and $N = 4$ charging stations.
3. Scenario III: We analyze how the results in terms of makespan, total completion time of recharging process, and energy cost are affected by variations in the number of jobs K (changed in the range

15 ÷ 30), while varying the number of forklifts M (changed in the range 2 ÷ 8), and the number of charging stations N (changed in the range 2 ÷ 11).

Table 2 reports the parameters related to all of the jobs (i.e., identifier, priority, and processing duration in terms of time slots). Furthermore, Table 3 reports the initial and final state conditions for forklifts (i.e., setup completion time, initial and final state of charge of the on-board battery normalized with respect to energy consumed per slot by the forklift) and the initial availability of a fully charged battery in charging stations. In particular, as indicated in Table 3, we assume that, in each forklift, the battery is fully charged at the beginning of operations. In order to equally compare the energy cost of the schedules computed in different cases, we impose that the final conditions of on-board batteries are equal to the initial ones and the final number of available fully charged batteries is equal to the initial one. Consequently, we assume that, at the completion of the last handled job, each forklift takes on board a fully charged battery, allowing the charging station to totally charge the lastly unloaded batteries. Finally, Table 4 reports the parameters related to the batteries (minimum and maximum allowed state of charge normalized with respect to energy consumed per slot by the forklift), the unitary penalty costs, and the weighting factors of the objective function terms used in the optimization model.

Table 2. Job parameters.

Description	Symbol	Value
Job index	k	[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30]
Job priority	p_k	[30, 29, 28, 27, 26, 25, 24, 23, 22, 21, 20, 19, 18, 17, 16, 15, 14, 13, 12, 11, 10, 9, 8, 7, 6, 5, 4, 3, 2, 1]
Job processing duration	l_k	[9, 9, 9, 6, 3, 4, 8, 1, 3, 2, 5, 2, 9, 2, 2, 1, 4, 3, 4, 4, 1, 3, 8, 4, 4, 9, 5, 1, 9, 3]

Table 3. Forklifts and charging station parameters.

Description	Symbol	Value
Setup completion time slot for each forklift	c_0^m	[0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
Initial state of charge of the on-board battery for each forklift	b_0^m	[10, 10, 10, 10, 10, 10, 10, 10, 10, 10]
Final state of charge of the on-board battery for each forklift	b_f^m	[10, 10, 10, 10, 10, 10, 10, 10, 10, 10]
Initial availability of a fully charged battery in charging stations	a_{nt}	1, $\forall n \in \mathcal{N}$, $\forall t \in \mathcal{T}$

Table 4. Scenario parameters.

Description	Symbol	Value
Fully charged battery capacity	b_{max}	10
Minimum battery capacity	b_{min}	1
Penalty unitary cost related to the job makespan	q_m	1
Penalty unitary cost related to the job ordering	q_p	1
Penalty unitary cost related to the battery recharging completion time	q_r	1
Weighting factors of the objective function terms in the first-step optimization	μ^I, μ^{II}	1/2, 1/2 in case I.a, scenario II and III 1, 0 in case I.b
Weighting factors of the objective function terms in the second-step optimization	π^I, π^{II}, π^{III}	1/3, 1/3, 1/3 in case I.a, scenario II and III 1, 0, 0 in case I.b

We further assume that the energy cost is time-dependent. In particular, we consider a time-of-use (TOU) pricing [47], where two different tariffs are applied over the planning horizon divided into seven time frames. We assume that the on-peak electricity rate is two times the off-peak electricity rate. Figure 6 shows in detail the unitary energy cost per slot, normalized with respect to the off-peak tariff.

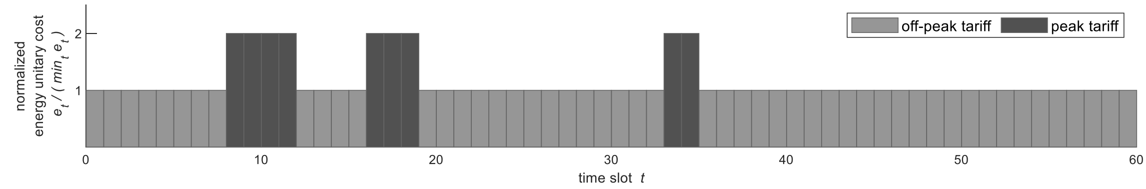

Figure 6. Normalized energy unitary cost versus time.

Finally, we highlight that the proposed two-step optimization model was implemented and solved in the MATLAB environment integrated with the SCIP (Solving Constraint Integer Programs) tool [48]. All of the presented computations were executed on a PC equipped with a 4.0 GHz Intel Core i7 CPU and 16 GB RAM. The computational runtime over all of the simulations ranged between 0.5 s to 50 min.

4.2. Results and Discussion

First, we analyze the schedules obtained by applying the proposed method to scenario I, which are illustrated in Figures 7–10 and Table 5.

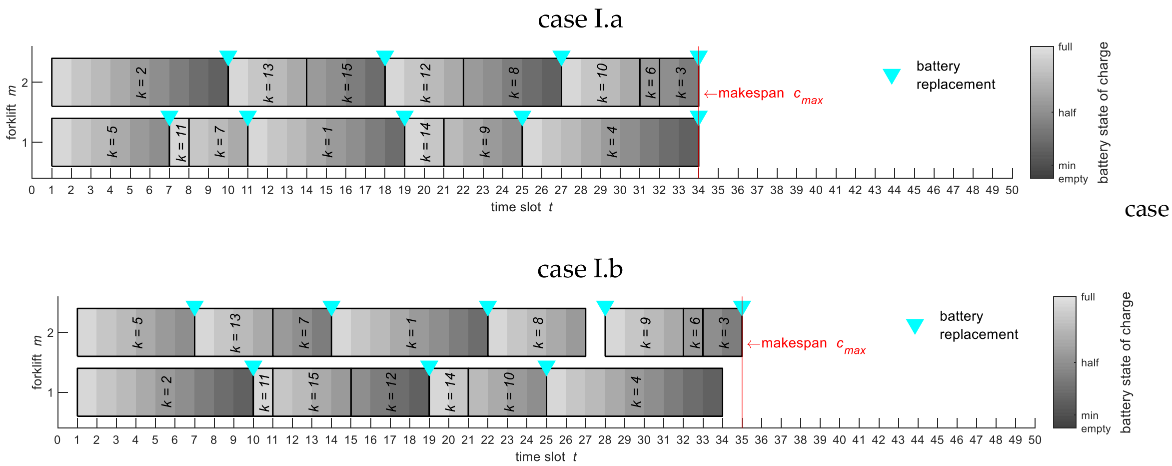

Figure 7. Gantt chart of jobs and discharging/replacement diagrams of batteries on each forklift.

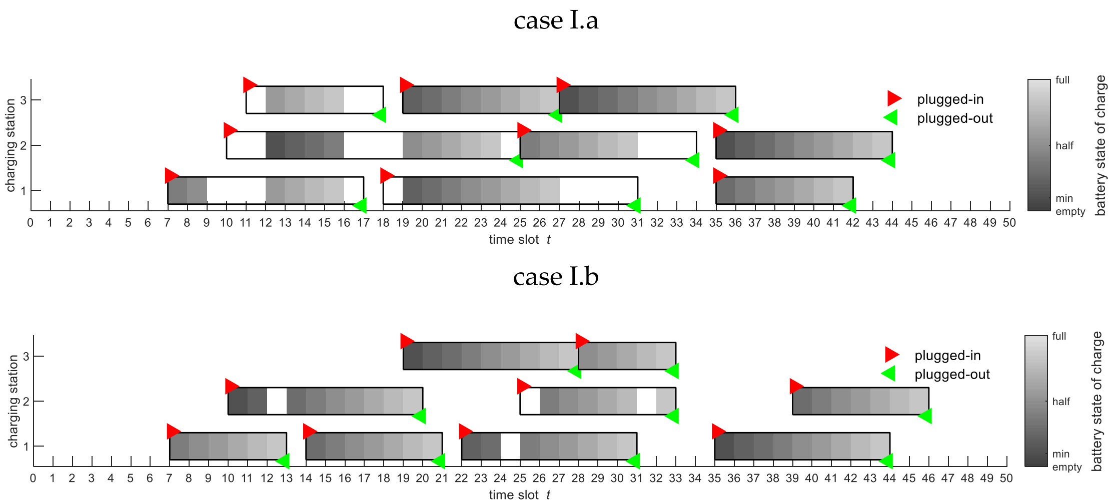

Figure 8. Scheduling of recharging operations and charging diagram of batteries on each charging.

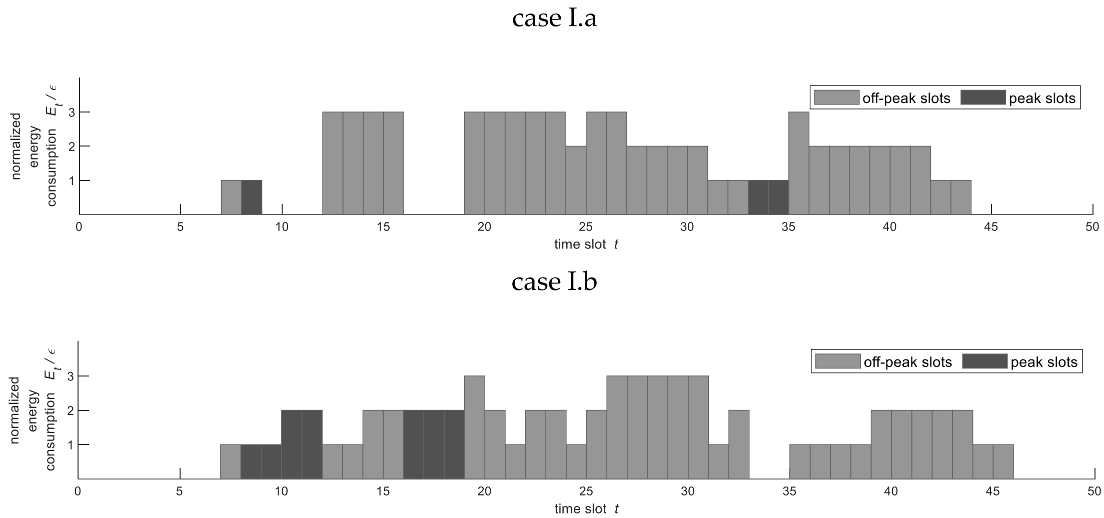

Figure 9. Profile of normalized energy consumption.

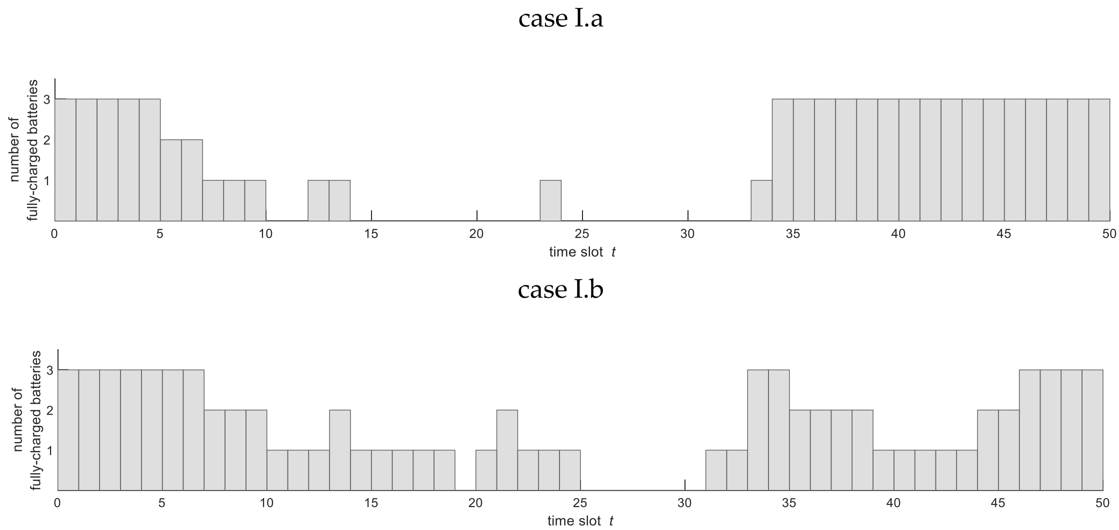

Figure 10. Number of available fully charged batteries.

Table 5. Comparison of analyzed cases in Scenario I and II.

	Case I.a	Case I.b	Case II.a	Case II.b
Makespan: c_{max}	34	35	24	24
Recharging process completion time: r_{max}	44	46	34	33
Normalized energy cost: $EC/(\epsilon \min_t e_t)$	69	77	74	67

In particular, Figure 7a,b show the Gantt chart of handled jobs and, for each forklift, the discharging/replacement diagrams of batteries for both cases of analysis. It is apparent from Figure 7a,b that jobs are handled in accordance with equal sequences, whilst the makespan is slightly different in cases I.a and I.b (as shown in the second row of Table 5). We also highlight that forklifts generally replace batteries at different time slots. Figure 8a,b provide details about the schedules of the recharging operations for both cases of analysis. The charging process begins when the unloaded battery is plugged in the available charging station and ends when the battery is unplugged. From Figure 8a, it is evident that, in case I.a, the charging station is not switched on over all of the plugged-in time slots. This allows charging stations to effectively acquire energy during low-cost time slots, resulting in a smart and energy-cost-saving-oriented scheduling. Conversely, from Figure 8b it is evident that, in case I.b, the charging process is generally active while batteries are plugged in the charging stations. Moreover, we remark that, in both cases I.a and I.b, the last recharging cycle corresponds to the charging process of batteries used by forklifts to handle the last jobs of their operation sequences. This ensures that the final state of charge in each battery (both on-board batteries on forklifts and auxiliary batteries in the charging station) is equal to the initial one, resulting in an equal overall consumption of energy in both cases of analysis.

On the other hand, the profiles of the overall energy consumed over time by the charging stations are different in cases I.a and I.b, as highlighted in Figure 9a,b. In particular, we note that the amount of energy acquired during on-peak time slots is greater in case I.b than in case I.a. As a result, the overall energy cost for the recharging operations is lower in case I.a than in case I.b (namely, 11.6%, as shown in the fourth row of Table 5).

Finally, Figure 10a,b show the number of available fully charged batteries over time slots for both cases of analysis. In both cases, the profiles are similar. In particular, at the beginning of the planning horizon (when the forklifts begin their operation with the initial fully charged batteries), such a number is kept at the highest level (i.e., equal to 3). In the middle (when the forklifts require recurrent battery replacements to finalize their operations), it achieves the lowest level (i.e., equal to 0). In the final portion of the planning horizon, the number of available fully charged batteries returns to be at the highest level. However, such a return is reached sooner in case I.b than in case I.a (as shown in the third row of Table 5).

Second, we assess the performance of the proposed method in scenario II and we compare the corresponding results with respect to scenario I.a. In particular, Figure 11a,b show the Gantt chart of handled jobs and, for each forklift, the discharging/replacement diagrams of batteries for the two cases of analysis II.a and II.b. Comparing Figures 7a and 11a, it is apparent that the higher the number of forklifts, the lower the makespan (as shown in the second row of Table 5). Conversely, Figure 11a,b show that, by increasing the number of charging stations from $N = 3$ to $N = 4$, no improvement in the makespan occurs (as reported in the second row of Table 5): In effect, in cases II.a and II.b, the jobs are handled in accordance with the same sequences and the battery replacement occurs in the same time slots.

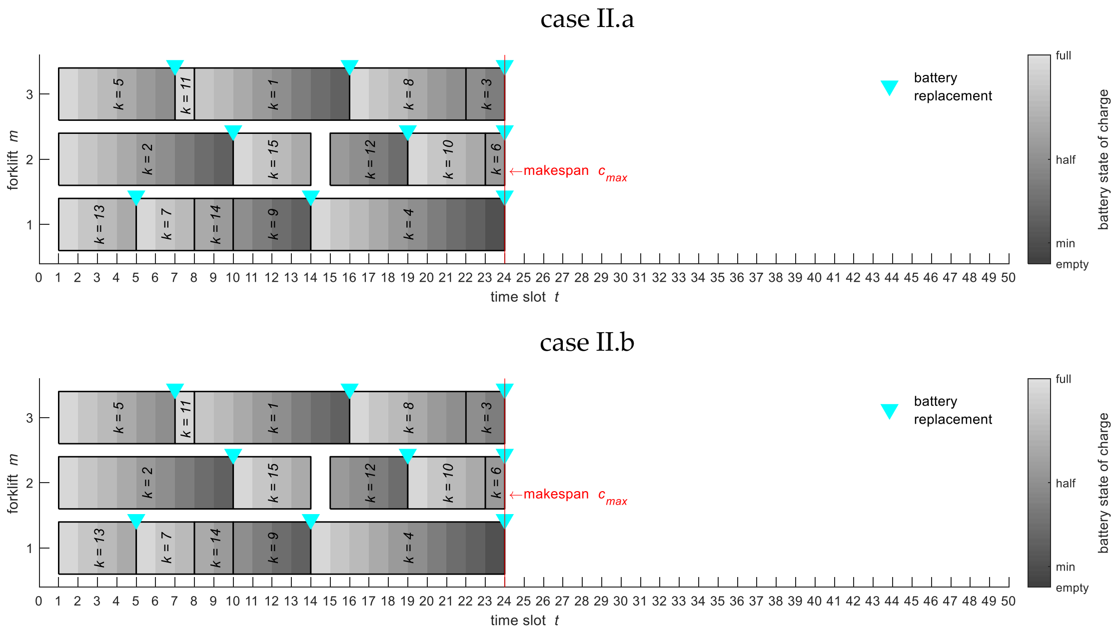

Figure 11. Gantt chart of jobs and discharging/replacement diagrams of batteries on each forklift.

Subsequently, Figure 12a,b provide details about the schedules of the recharging operations for the two cases of analysis related to scenario II. Comparing Figures 8a and 12a,b, it is evident that the charging stations are not switched on over all of the plugged-in time slots. It is apparent from Figures 8a and 12a that the higher the number of forklifts, and thus the lower the makespan, the lower the overall completion time of the recharging process (as shown in the third row of Table 5).

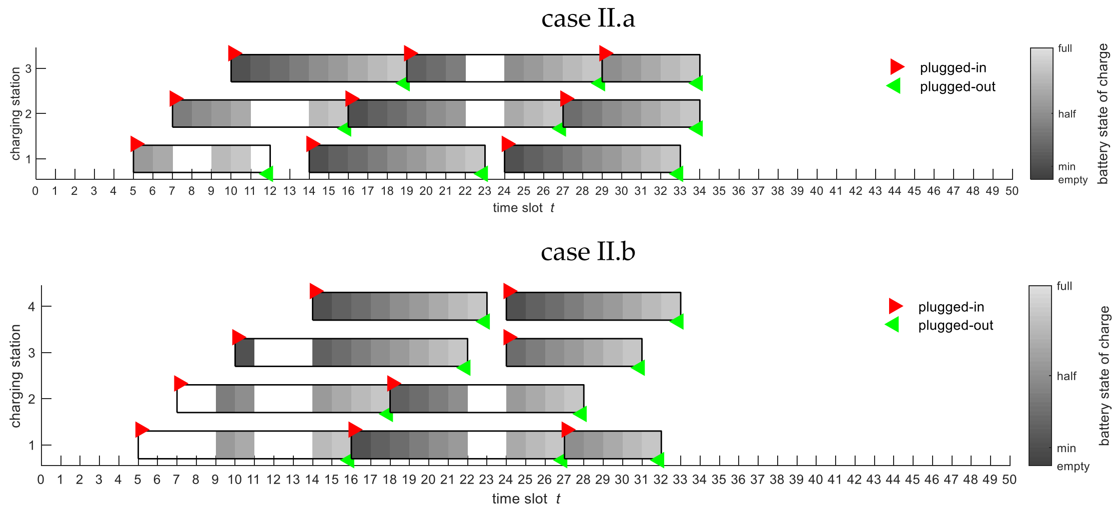

Figure 12. Scheduling of recharging operations and charging diagram of batteries on each charging station.

Similarly, it is evident from Figure 12a,b that, by increasing the number of charging stations from $N = 3$ to $N = 4$, the overall completion time of the recharging process is reduced, since unplugged batteries find free charging stations sooner.

Furthermore, the profiles of the overall energy consumed over time by the charging stations are different in cases I.a, II.a, and II.b, as highlighted in Figures 9a and 13a,b. In particular, we note that the amount of energy acquired during on-peak time slots is greater in case II.a than in case I.a, since, in case II.a, the batteries are required to be recharged within a shorter period (where the energy tariffs are less convenient) than in case I.a. Conversely, in case II.b, the amount of energy acquired during on-peak time slots is lower than in case II.a; even though the duration of the recharging process is similar in both cases, the availability of more charging stations in case II.b allows the avoidance of acquiring energy during on-peak times, differently from case II.a. As a result, the overall energy cost for the recharging operations is lower in case II.b than in cases II.a and I.a (namely, 3% and 9%, as shown in the fourth row of Table 5).

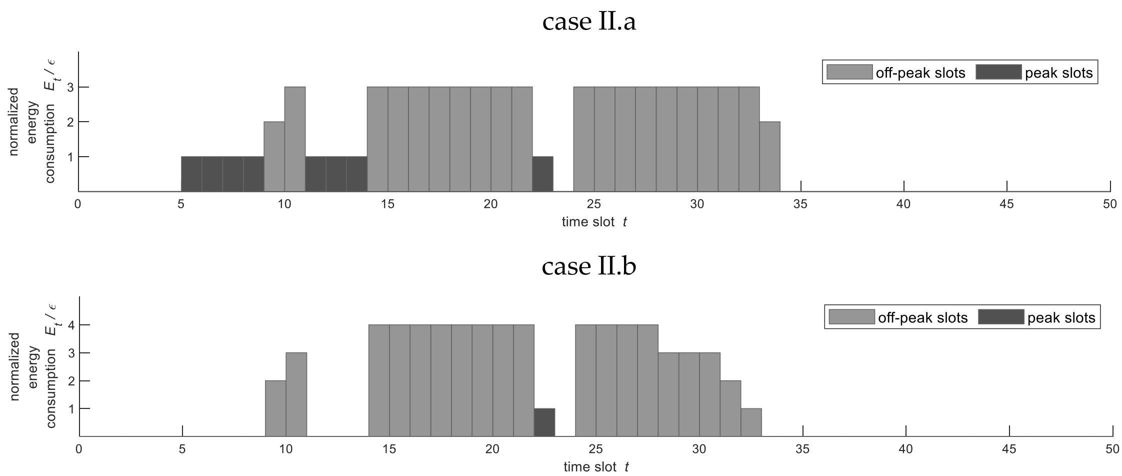

Figure 13. Profile of normalized energy consumption.

Finally, Figure 14a,b show the number of available fully charged batteries over time slots for the two cases of analysis related to scenario II. Comparing Figures 10a and 14a,b, we note that, at the beginning of the planning horizon (when the forklifts begin their operation with the initial fully charged batteries), such a number is kept at the highest level (i.e., equal to 3 and 4 for cases I.a, II.a, and II.b, respectively). In the middle (when the forklifts require recurrent battery replacements to finalize their operations), it achieves the lowest level (i.e., equal to 0, that is, all of the charging stations are busy). In the final portion of the planning horizon, the number of available fully charged batteries returns to be at the highest level (i.e., all of the charging stations become available again). However, such a return is reached sooner in case II.b than in case II.a, where, in turn, it is reached sooner than in case I.a (as shown in the third row of Table 5).

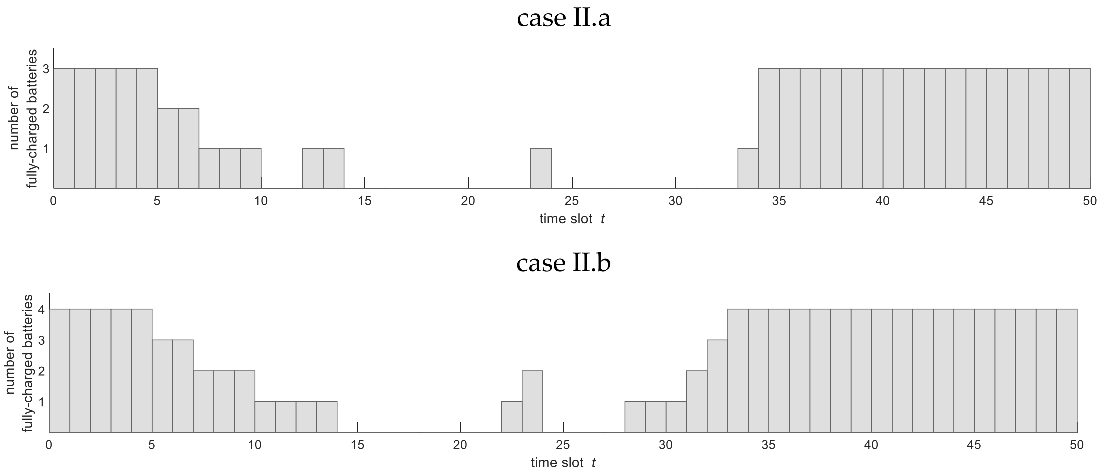

Figure 14. Number of available fully charged batteries.

Third, we assess the performance of the proposed method in scenario III, where a more complex setup (i.e., greater number of jobs, forklifts, charging stations, etc.) is considered. The obtained results are illustrated in Figures 15–18.

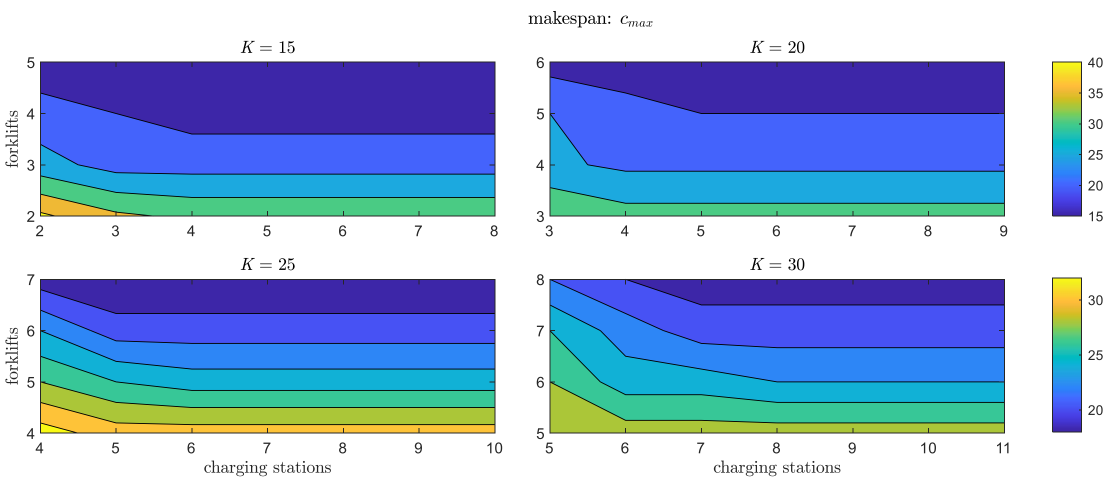

Figure 15. Contour plot of the makespan as a function of the number of forklifts and charging stations for different numbers of jobs.

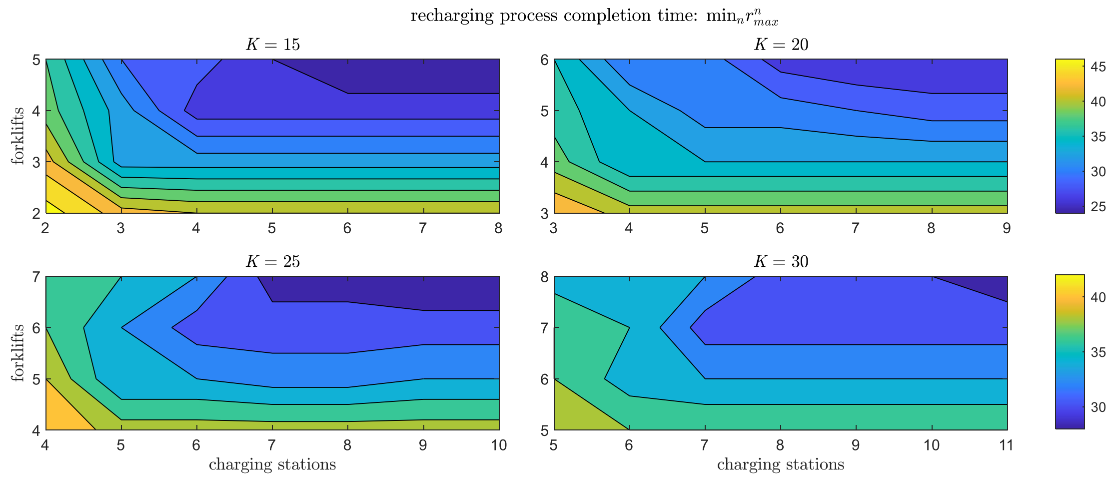

Figure 16. Contour plot of the recharging process completion time as a function of the number of forklifts and charging stations for different numbers of jobs.

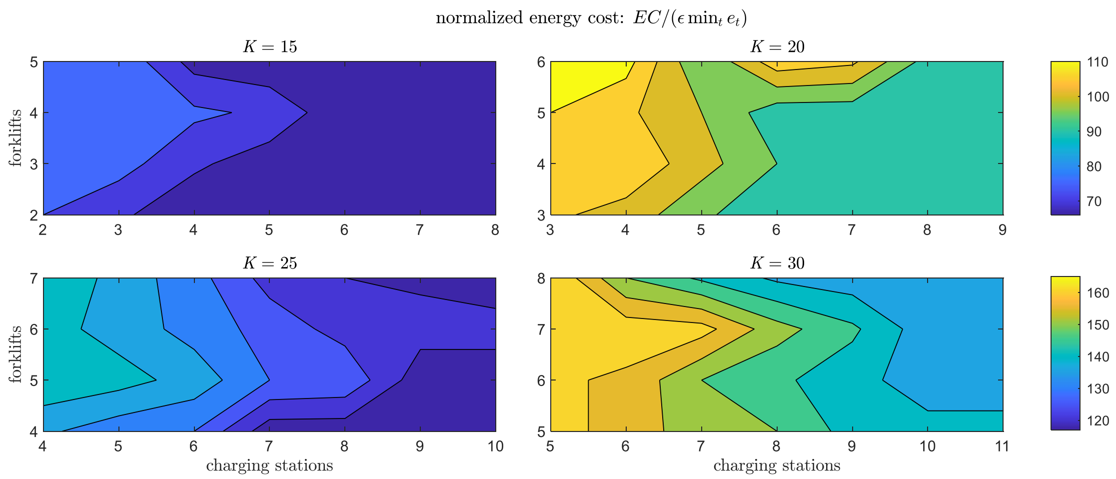

Figure 17. Contour plot of energy cost as a function of the number of forklifts and charging stations for different numbers of jobs.

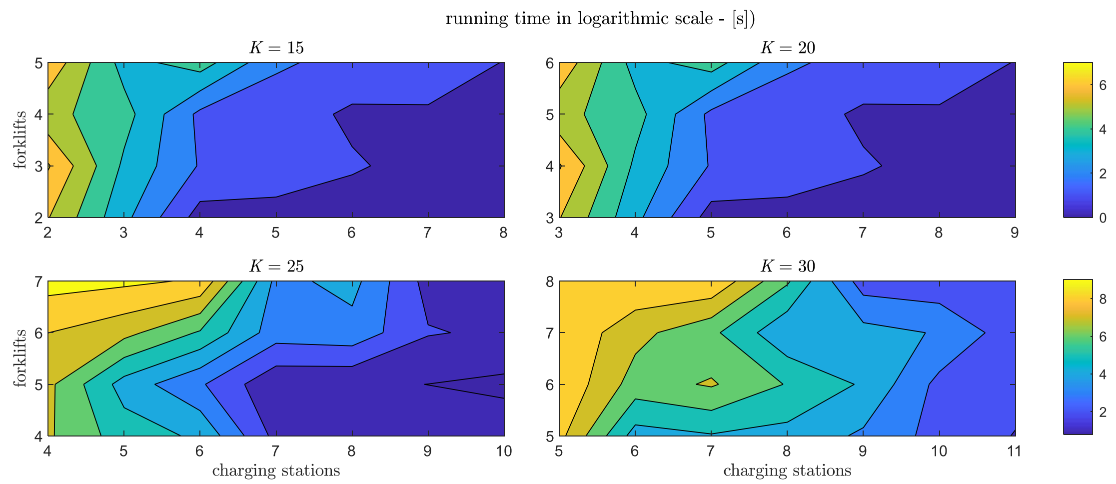

Figure 18. Contour plot of the run time as a function of the number of forklifts and charging stations for different numbers of jobs.

In particular, Figure 15 shows the makespan as a function of the number of forklifts and charging stations for different numbers of jobs. It is apparent that, for a given number of jobs, the makespan could not be indefinitely reduced by increasing the number of forklifts. Similarly, for a given number of jobs and forklifts, there is no convenience in increasing the number of charging stations above a given value. We remark that Figure 15 shows that such a value corresponds approximatively to the number of forklifts.

Furthermore, Figure 16 shows the recharging process completion time as a function of the number of forklifts and charging stations for different numbers of jobs. It is apparent that for a given number of jobs and forklifts, the recharging process could not be indefinitely reduced by increasing the number of charging stations. Figure 16 shows that such a value is roughly just above the number of forklifts.

In addition, Figure 17 shows the energy cost as a function of the number of forklifts and charging stations for different numbers of jobs. It is apparent that for a given number of jobs, the energy cost could be reduced by increasing both the number of forklifts and charging stations. For a given number of jobs and forklifts, there is no convenience in increasing the number of charging stations above a given value. However, when the number of forklifts is low, the minimum energy cost is achieved with a number of charging stations that is approximatively two times the number of forklifts (e.g., for $K = 25$ and $M = 4 \div 5$, the minimum energy cost is achieved with $N = 8 \div 9$). Conversely, when the number of forklifts is higher, the minimum energy cost is achieved with a number of charging stations that corresponds approximatively to the number of forklifts (e.g., for $K = 25$ and $M = 7$, the minimum energy cost is achieved with $N = 8$).

Finally, even though the addressed optimization problem arises at a planning level (where the run time is less critical than in operational management), we provide an analysis of run time. In particular, Figure 18 shows the run time required by the proposed optimization model as a function of the number of forklifts and charging stations for different numbers of jobs. Given a number of forklifts and charging stations, it is evident that the run time grows as the number of jobs grows. Conversely, for a given number of jobs, the lower the number of forklifts and charging stations, the higher the run time. This is due the fact that, with limited resources (i.e., both forklifts and charging stations), the search for the optimal scheduling is carried out on a narrow decision space.

As a final remark, we note that Figures 15–17 show that the proposed model could be used as a decision support tool in defining the optimal configuration of the resources (e.g., number of forklifts and charging stations) deployed in the warehouse in order to schedule jobs in a sustainable and cost-efficient perspective.

5. Conclusions

Recently, sustainability in warehouses has gained importance both in industrial and academic research, with the main investigated issue being energy management and its potential effects both on organizations (economic advantages) and collectivity (environmental advantages). In this context, the approach developed in this manuscript allows the reduction of the impact of electric MMHE recharging on the warehouse performance from both an economic and a sustainable perspective. The approach allows us to automatically determine a scheduling strategy minimizing the cost of electric MMHEs under dynamic energy pricing. The proposed approach ensures equivalent performance (i.e., makespan) of traditional strategies and contributes to leveling of the peak load and reshaping of the demand curve, thus increasing sustainability thanks to the overall cost and carbon emission level reduction.

From a managerial point of view, the adoption of the approach could lead to jointly achieving two goals: An economic advantage, obtained by means of the minimization of the electricity cost, and a competitiveness one, based on the sustainable approach. The economic advantage could be further amplified by adopting on-line control systems for smart energy consumption already employed in other contexts (e.g., homes, municipalities, public buildings, etc.). At the same time, real-time data could support the sustainability assessment (e.g., the evaluation of reduced GHG emissions).

There are still substantial gaps in this work that require further investigation. There is a need for generalizing the problem to take into account different picking strategies. Moreover, the approach should be generalized in order to be suitable for application to warehouses where multiple material handling strategies are adopted. Future research will also be focused on assessing the computational complexity of the proposed approach, also in comparison with alternative heuristic resolution approaches. Furthermore, future developments will be devoted to applying the presented approach to a real industrial case study to show its actual applicability and performance. Finally, further work may incorporate the proposed method with a receding horizon mechanism for real-time scheduling of jobs and battery recharging processes.

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