



International Conference on Industry 4.0 and Smart Manufacturing (ISM 2019)

A Control Strategy for Smart Energy Charging of Warehouse Material Handling Equipment

Raffaele Carli^a, Salvatore Digiesi^b, Mariagrazia Dotoli^a, Francesco Facchini^{b*}

^aDepartment of Electrical and Information Engineering, Polytechnic University of Bari, Via E. Orabona, 4 – 70125 BARI - Italy

^bDepartment of Mechanics, Mathematics and Management, Polytechnic University of Bari, Via E. Orabona, 4 – 70125 BARI - Italy

* Corresponding author. Tel.: +39-080-5963612. E-mail address: francesco.facchini@poliba.it

Abstract

The common driver of the ‘green-warehouse’ strategy is based on the reduction of energy consumption. In warehouses with ‘picker-to-part’ operations the minimization of energy due to material handling activities can be achieved by means of different policies: by adopting smart automatic picking systems, by adopting energy-efficient material handling equipment (MHE) as well as by identifying flexible layouts. In most cases, these strategies require investments characterized by high pay-back times. In this context, management strategies focused on the adoption of available equipment allow to increase the warehouse productivity at negligible costs. With this purpose, an optimization model is proposed in order to identify an optimal control strategy for the battery charging of a fleet of electric mobile MHE (e.g., forklifts), allowing minimizing the economic and environmental impact of material handling activities in labor-intensive warehouses. The resulting scheduling problem is formalized as an integer programming (IP) problem aimed at minimizing the total cost, which is the sum of the penalty cost related to makespan over all the material handling activities and the total electricity cost for charging batteries of MHE. Numerical experiments are used to investigate and quantify the effects of integrating the scheduling of electric loads into the scheduling of material handling operations.

© 2020 The Authors. Published by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

Peer-review under responsibility of the scientific committee of the International Conference on Industry 4.0 and Smart Manufacturing.

Keywords: green warehouse; material handling activity; warehouse energy management; industrial/manufacturing demand side management; battery smart charging; optimization; integer programming.

1. Introduction

Green warehousing is a relatively new approach for implementing ‘greening activities’ in warehouses and distribution centers [1]. A sustainable approach allows to bring economic, environmental and social benefits beyond the supply chain. Results of recent market surveys show that a sustainable approach allows to increase the brand fidelity, stakeholder satisfaction as well as the flexibility of companies to quickly respond to market’s changes. Consistently with this approach, the minimization of resources and the maximization of productivity are the key targets of most competitive companies. In this context, the warehousing activities represent key nodes in many supply chains. According to Dhooma and Baker [2], the logistics cost due to energy consumption represents 20% of

the overall energetic cost required by supply chains, and this value is expected to significantly increase in the future, according to the energy consumption values in the industrial sector predicted for the next twenty years [3]. Therefore, an increasing number of companies and researchers are paying more attention to the environmental impact of warehousing activities on their supply chains [2]. This is also being favored by the development of Information and Communications Technologies (ICT) [4]-[5] as well as by the adoption of I4.0 technologies [6]-[7]. In warehouses, energy is required for two different macro-categories of activities: the first concerns the energy consumption due to direct movements of product or materials by both fixed material handling equipment (MHE), such as conveyor systems and automated cranes, and mobile MHE, such as forklift, trucks, etc. The second category includes

2351-9789 © 2020 The Authors. Published by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

Peer-review under responsibility of the scientific committee of the International Conference on Industry 4.0 and Smart Manufacturing.

10.1016/j.promfg.2020.02.041

energy consumption due to warehouse facilities like heating, lighting, and air conditioning of the building as well as power supply of computer systems, office equipment and miscellaneous equipment such as catering appliances. It is very interesting to remark that the energy consumed for these latter categories rapidly changed over time: the studies conducted by [2] upgraded on the basis of the recent statistics disclosed by ‘European Materials Handling Federation’ (<https://www.fem-eur.com/>) showed, in the last twenty years, an increase of around 77% of energy consumption due to MHE (Fig. 1). Consistently with this trend, it is clear that energy consumption is a significant issue for MHE both under the economic and environmental perspectives. Therefore, energy efficiency has become one of the top priorities for industry as well as for customers.

While on one hand the overall energy consumption of warehouses due to material handling activities increases over time, on the other hand the adoption of fixed MHE is outstripping the adoption of mobile MHE, which means that in modern warehouses the ‘part-to-picker’ strategies are more widespread than ‘picker-to-part’ strategies. Therefore, an increasing attention is being devoted by the scientific literature on warehouses to which products are moved from the storage area to the picking bays by automatic equipment when no forklift is adopted. Even if this research stream is very interesting as regards productivity aspects, in most cases it is not justified under an energetic perspective, since from an energetic point of view mobile MHE are more energy intensive than of fixed MHE, therefore actions in this field could lead to great benefits.

Although different approaches were developed in the scientific literature with the aim of reducing the energy consumption of forklifts in material handling operations, many aspects are not yet deeply analyzed. In particular, as mentioned, most studies on energy consumption are focused on ‘part-to-picker’ strategies in which automated storage and retrieval system (AS/RS) warehouses are widely adopted. In these cases, the material handling activities can be regarded as systematic, continuous and fully automated, and easily described by mathematical models. In the case of ‘picker-to-part’ strategies, a more complex theoretical formulation is required.

Further considerations concern the approach adopted in ‘green-warehouse’, which is more focused on energy issues related to electric demand of facilities (e.g., lighting, heating, cooling, ventilation, etc.) rather than MHE charging. A lack of studies on energy consumption due to material handling activities is highlighted in [8]. Similarly, as shown in the literature review provided in the next section, there is a lack on strategies for managing the charging of forklifts. In particular, there are very few studies in which the charging schedule of forklifts is optimized under the economic and environmental perspectives. Nevertheless, the active management of electricity demand, commonly known as demand side management (DSM), has been recognized as an effective approach to significantly improve benefits also for large electricity consumers such as power-intensive industries and manufacturing companies [9]. Currently, renovation in 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).

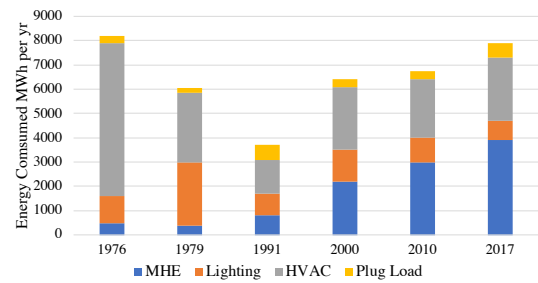


Fig. 1. Energy consumed in warehouses by end-use category 1976-2017.

Consequently, both the day-ahead and real-time scheduling of load profile results in a beneficial impact on the consumption of industrial users as they respond to pricing signals while minimizing energy expenses [9]. Similarly, manufacturing companies can minimize costs by implementing demand-side management for their production scheduling, considering time-dependent electricity costs [10].

Consistently with the observations mentioned above, the existing gaps in the scientific literature on warehouses could be filled through the following actions:

- (RQ1) To provide a model integrating the job scheduling and the energy consumption profile of MHE in picking processes characterized by a ‘picker-to-part’ strategy;
- (RQ2) To optimize the charging schedule of MHE from an economic perspective under a dynamic energy pricing.

Therefore, the aim of the proposed study is to develop an optimization model for identifying an optimal battery-charging schedule of a fleet of electric mobile MHE that jointly minimizes the overall cost of electricity and the makespan of material handling activities in a labor-intensive warehouse. The resulting scheduling problem is formalized as an integer programming (IP) problem aimed at minimizing the total cost, which is the sum of the penalty cost related to makespan over all the material handling activities and the total electricity cost for charging batteries of MHE. Numerical experiments are used to investigate and quantify the effects of integrating the scheduling of electric loads into the scheduling of material handling operations.

The remainder of the paper is organized as follows: a brief review of management of energetic issues related to handling activities in warehouses is presented in Section 2; in Section 3 the model methodology is introduced; the results obtained by applying the model to numerical experiments are reported in section 4; finally, conclusions of this work are in Section 5.

2. Literature review

In the scientific literature, many studies address the energy minimization due to material handling processes. In particular, it is possible to identify two different categories of picking strategies: ‘picker-to-part’ and ‘part-to-picker’. Generally, the first one is based on the adoption of manual forklifts (e.g. rider trucks, hand trucks, narrow aisle trucks, etc.) in traditional indoor warehouses equipped with industrial shelves system; the

second one is based on the adoption of AS/RS in automatic warehouses. In addition, it is possible to identify, for both picking strategies, three different approaches, aiming at reducing the material handling energy consumption while ensuring a high productivity:

- the first approach is focused on 'logistics' aspects; in these cases, issues related to the allocation of items in the warehouse are deeply investigated. Consistently with this approach, the developed models allow to identify the best items-allocation, in order to minimize the path required by forklifts for picking and/or stocking operations, under deterministic and stochastic conditions;
- the second approach concerns 'organizational' aspects; in these cases, different order-scheduling strategies, for both inbound/outbound items, are identified in order to minimize the time required for materials handling activities. The developed models allow to identify the best sequencing of inbound/outbound orders, consistently with the characteristics and allocation of items to be picked/stored, and the forklift features (e.g., delivery time);
- the third approach is focused on 'technological' aspects; innovative technologies available on the market are considered, such as energy recovery systems allowing to reduce the forklifts energy consumption ensuring, at the same time, high performance. Studies developed in this area are generally oriented to evaluating the economic and environmental issues related to the adoption (purchasing and management) of innovative MHEs.

Consistently with the logistic approach, Bortolini et al. [11] propose a bi-objective model to optimize the scheduling in automatic warehouses. Results highlight the possibility to minimize the energy consumption ensuring low cycle times. In particular, in the work case, a reduction of about 12.66% of energy requirement is evaluated with a much smaller increase of single-command cycle time of about 2.52% [11]. In Malaguti et al. [12], a decision model is developed in order to optimize the allocation of goods in a retail company operating through e-commerce. Results show the effectiveness of the model to support the decision makers in identifying the proper allocation of goods under deterministic conditions [12]. A storage space allocation model that considers the availability of a forklift fleet in a warehouse is introduced in [13]. The application of the model to a numerical example shows that the identified location assignment allows to reduce the overtime working hours on days increasing, at the same time, the volume of receiving and shipping out products [13].

The order sequencing issue plays a central role in reducing the energy consumption due to material handling in warehouse/s. Ene et al. [14] adopt a Genetic Algorithm (GA) allowing to optimize both the routing and batching process in picker-to-part warehouse systems. Results show that the GA provides efficient solutions to the problem ensuring significant energy savings corresponding to 23.5% in the numerical experiment [14]. An innovative sorting process in AS/RS warehouse was recently developed in order to minimize the spread of orders in the release sequence so that picking orders are quickly assembled at their packing stations [15]. Results show that the model provides effective solutions in a short

computational time. A very interesting investigation that leads to a significant reduction of energy consumption in a warehouse/s, based on a part-to-picker approach, is developed on systems known as 'Kiva'. These processing systems are characterized by mobile robots that hoist racks and bring them directly to stationary pickers. The computational study conducted on this system shows a significant reduction of total energy consumption due to material handling is observed [16].

Considering the 'technological' aspects, Minav et al. [17] prove that the recovery of energy from hydraulic system of a forklift, adopting an industrial electric drive and an electrical servo motor, is possible. The system was tested on real cases, and the results show an increase of efficiency of around 20% compared with traditional systems [17]. A Potential Energy Recovery System (PERS) is introduced in an electro-hydraulic industrial forklift. The energy-saving ratios were calculated for different test arrangements as functions of speed and payload, and the average achieved energy-saved ratio varies between 17 and 50% [18].

Consistently with the above discussed approaches, the application of intelligent DSM to the industrial/manufacturing energy users is rapidly gaining momentum in the scientific research and industry [9]. Similarly to the residential DSM, where energy users schedule their domestic activities in accordance with demand response mechanisms [19], load scheduling has recently attracted significant attention in the industrial/manufacturing sector. Since the emerging paradigm of smart grid requires industries/manufacturing companies to pay dynamic time-variant electricity costs, it is profitable for such consumers to reschedule and shift the energy demand to periods with low rates [20]. On the other hand, industrial/manufacturing DSM strongly integrates operations scheduling and energy management, which requires detailed knowledge of processes as well as modeling of power market. Several studies investigate the technical and economic potential of industrial/manufacturing companies to provide DSM. For instance, Moon and Park [10] propose a model for the flexible job-shop problem by considering time-dependent and machine-dependent electricity costs. The proposed scheduling problem aims at minimizing the makespan, while reducing the electricity cost [10]. Several other contributions are available in the scientific literature on DSM in industry [20]-[23]. In case of warehouses, DSM systems have mainly been studied for automated warehouses [24].

Summing up, to the best of authors' knowledge, no studies propose decision-making approaches to effectively determine the charging schedule of forklifts for material handling activities in labor-intensive warehouses.

In the next section an optimization model for identifying an optimal battery-charging schedule of a fleet of forklifts that jointly minimizes the overall cost of electricity and the makespan of material handling activities in a labor-intensive warehouse is defined.

3. System modeling and problem formulation

The scheduling of forklift activities of a green warehouse considering the smart charging of batteries is formulated as follows.

3.1. Assumptions

The following assumptions are made:

1. Each job is composed by an uninterruptible and ordered sequence of picking operations.
2. Each forklift can process only one job at a time. The related processing time is known and independent from forklift and job execution order.
3. The processing time of each job is less than the full-charged battery capacity.
4. Battery usage on each forklift is zero during idling times.
5. All the jobs are completed within the considered planning horizon.
6. There are no overlapping constraints between forklifts performing different jobs.
7. Change of battery is done in a neglectable time on any forklift.
8. Battery charging is an interruptible load and is performed with a fixed energy rate.
The pricing of energy bought from the power grid is variable during the planning window but known ahead of time.

3.2. Indices and sets

The following notation is used:

j, j'	activities including jobs ($j \in \mathcal{J}$), forklift initial setup ($j = 0$) and final setup ($j = J + 1$)
m	forklifts ($m \in \mathcal{M}$)
t	time slots ($t \in \mathcal{T}$)
\mathcal{J}	set of jobs $\{1, \dots, j, \dots, J\}$
\mathcal{M}	set of forklifts $\{1, \dots, m, \dots, M\}$
\mathcal{T}	planning horizon $\{1, \dots, t, \dots, T\}$
\mathcal{B}	set of levels of battery capacity

3.3. Parameters

The following parameters are used:

J	number of jobs
M	number of electric forklift
T	number of time slots
L	a large number
p_j	Processing duration of job j
c_{0m}	setup completion time of forklift m
q	penalty unitary cost
b_{max}	fully-charged battery capacity
b_{min}	minimum battery capacity
b_{0m}	capacity of the battery in forklift m at the beginning of the planning horizon
n_0	number of available fully-charged batteries at the beginning of the planning horizon
ϵ	amount of energy required to charge one battery in one time slot
e_t	energy unitary cost at time slot t
π^I	weighting factor of the makespan term in the objective function
π^{II}	weighting factor of the energy cost term in the objective function

3.4. Decision variables

The following decision variables are used:

x_{jm}	1 if forklift m is selected for job j ; 0 otherwise
$y_{jj'm}$	1 if activity $j \in \mathcal{J} \cup \{0\}$ immediately precedes activity $j' \in \mathcal{J} \setminus \{j\} \cup \{J + 1\}$ on forklift m ; 0 otherwise
$y_{jj'}$	1 if activity $j \in \mathcal{J} \cup \{0\}$ immediately precedes activity $j' \in \mathcal{J} \setminus \{j\} \cup \{J + 1\}$ on the same forklift; 0 otherwise
s_{jm}	starting time of job $j \in \mathcal{J}$ on forklift m
c_{jm}	completion time of job $j \in \mathcal{J}$ on forklift m
d_{jm}	idling time before processing job $j \in \mathcal{J}$ on forklift m
s_j	starting time of job $j \in \mathcal{J}$
c_j	completion time of job $j \in \mathcal{J}$
c_{max}	maximum completion time over all the jobs (makespan)
PC	penalty cost related to makespan
z_j	1 if forklift replaces its battery with a fully-charged one at the beginning of job $j \in \mathcal{J}$; 0 otherwise
$\beta_{jj'}$	capacity of battery at the beginning of job $j' \in \mathcal{J}$ in case this is preceded by activity $j \in \mathcal{J} \setminus \{j'\} \cup \{0\}$
b_j	capacity of battery at the beginning of job $j \in \mathcal{J}$ taking into account the eventual battery replacement
σ_{jt}	1 if t is the starting time of the recharging window for the battery replaced at the beginning of job $j \in \mathcal{J}$; 0 otherwise
γ_{jt}	1 if t is the completion time of the recharging process for the battery replaced at the beginning of job $j \in \mathcal{J}$; 0 otherwise
δ_{jt}	1 if t is within the recharging window for the battery replaced at the beginning of job $j \in \mathcal{J}$; 0 otherwise
ρ_{jt}	1 if the battery replaced at the beginning of job $j \in \mathcal{J}$ is actually recharged in time slot t ; 0 otherwise
E_t	energy for charging batteries of forklifts at time slot t
EC	overall energy cost for charging batteries of forklifts over the planning horizon

3.5. Optimization model

The proposed mathematical model is defined as follows:

$$\min(\pi^I PC + \pi^{II} EC) \quad (1)$$

s.t.

$$\sum_{m \in \mathcal{M}} x_{jm} = 1, \forall j \in \mathcal{J} \quad (2)$$

$$s_{jm} + c_{jm} \leq x_{jm} L, \forall j \in \mathcal{J}, \forall m \in \mathcal{M} \quad (3)$$

$$c_{jm} \geq s_{jm} + d_{jm} + p_j - (1 - x_{jm})L, \forall j \in \mathcal{J}, \forall m \in \mathcal{M} \quad (4)$$

$$s_{jm} \geq c_{jm} - (1 - y_{jj'm})L, \quad \forall j' \in \mathcal{J}, \forall j \in \mathcal{J} \setminus \{j'\} \cup \{0\}, \forall m \in \mathcal{M} \quad (5)$$

$$\sum_{j' \in \mathcal{J} \setminus \{j\} \cup \{0\}} y_{jj'm} = x_{jm}, \quad \forall j' \in \mathcal{J} \quad (6)$$

$$\sum_{j' \in \mathcal{J} \setminus \{j\} \cup \{j+1\}} y_{jj'm} = x_{jm}, \quad \forall j \in \mathcal{J} \quad (7)$$

$$\sum_{j \in \mathcal{J}} y_{0jm} = 1, \quad \forall m \in \mathcal{M} \quad (8)$$

$$\sum_{j \in \mathcal{J}} y_{j(j+1)m} = 1, \quad \forall m \in \mathcal{M} \quad (9)$$

$$y_{jj'} = \sum_{m \in \mathcal{M}} y_{jj'm}, \quad \forall j' \in \mathcal{J}, \forall j \in \mathcal{J} \setminus \{j'\} \cup \{0\} \quad (10)$$

$$c_j = \sum_{m \in \mathcal{M}} c_{jm}, \quad \forall j \in \mathcal{J} \quad (11)$$

$$s_j = \sum_{m \in \mathcal{M}} s_{jm}, \quad \forall j \in \mathcal{J} \quad (12)$$

$$c_{max} \geq c_j, \quad \forall j \in \mathcal{J} \quad (13)$$

$$PC = qc_{max} \quad (14)$$

$$\beta_{0j} = \sum_{m \in \mathcal{M}} b_{0m} y_{0jm}, \quad \forall j \in \mathcal{J} \quad (15)$$

$$\beta_{jj'} = (b_j - p_j) y_{jj'}, \quad \forall j' \in \mathcal{J}, \forall j \in \mathcal{J} \setminus \{j'\} \quad (16)$$

$$b_j = (1 - z_j) \sum_{j' \in \mathcal{J} \setminus \{j\} \cup \{0\}} \beta_{jj'} + z_j b_{max}, \quad \forall j \in \mathcal{J} \quad (17)$$

$$b_j \geq (p_j + b_{min}), \quad \forall j \in \mathcal{J} \quad (18)$$

$$\sum_{t \in \mathcal{T}} \sigma_{jt} = s_j z_j, \quad \forall j \in \mathcal{J} \quad (19)$$

$$\sum_{t \in \mathcal{T}} \gamma_{jt} \geq \sum_{t \in \mathcal{T}} \sigma_{jt}, \quad \forall j \in \mathcal{J} \quad (20)$$

$$\sum_{t \in \mathcal{T}} \sigma_{jt} + \sum_{t \in \mathcal{T}} \gamma_{jt} \leq z_j L, \quad \forall j \in \mathcal{J} \quad (21)$$

$$\sum_{t \in \mathcal{T}} \sigma_{jt} \leq 1, \quad \forall j \in \mathcal{J} \quad (22)$$

$$\sum_{t \in \mathcal{T}} \gamma_{jt} \leq 1, \quad \forall j \in \mathcal{J} \quad (23)$$

$$\delta_{jt} = \sum_{\tau=1}^t (\sigma_{j\tau} - \gamma_{j\tau}), \quad \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (24)$$

$$\rho_{jt} \leq \delta_{jt}, \quad \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (25)$$

$$\sum_{t \in \mathcal{T}} \rho_{jt} = z_j (b_{max} - \sum_{j' \in \mathcal{J} \setminus \{j\} \cup \{0\}} \beta_{jj'}), \quad \forall j \in \mathcal{J} \quad (26)$$

$$n_0 - \sum_{j \in \mathcal{J}} \delta_{jt} \geq 0, \quad \forall t \in \mathcal{T} \quad (27)$$

$$E_t = \epsilon \sum_{j \in \mathcal{J}} \rho_{jt} \quad (28)$$

$$EC = \sum_{t \in \mathcal{T}} e_t E_t \quad (29)$$

$$x_{jm} \in \{0,1\}, \quad \forall j \in \mathcal{J}, \forall m \in \mathcal{M} \quad (30)$$

$$y_{jj'm} \in \{0,1\}, \quad \forall j' \in \mathcal{J}, \forall j \in \mathcal{J} \setminus \{j'\} \cup \{0\}, \forall m \in \mathcal{M} \quad (31)$$

$$y_{jj'} \in \{0,1\}, \quad \forall j' \in \mathcal{J}, \forall j \in \mathcal{J} \setminus \{j'\} \quad (32)$$

$$s_{jm}, c_{jm}, d_{jm} \in \mathcal{T}, \quad \forall j \in \mathcal{J}, \forall m \in \mathcal{M} \quad (33)$$

$$s_j, c_j \in \mathcal{T}, \quad \forall j \in \mathcal{J} \quad (34)$$

$$z_j \in \{0,1\}, \quad \forall j \in \mathcal{J} \quad (35)$$

$$b_j \in \mathcal{B}, \quad \forall j \in \mathcal{J} \quad (36)$$

$$\beta_{jj'} \in \mathcal{B}, \quad \forall j' \in \mathcal{J}, \forall j \in \mathcal{J} \setminus \{j'\} \cup \{0\} \quad (37)$$

$$\sigma_{jt}, \gamma_{jt}, \delta_{jt}, \rho_{jt} \in \{0,1\}, \quad \forall j \in \mathcal{J}, \forall t \in \mathcal{T} \quad (38)$$

The objective in (1) is minimizing the total cost, which is the sum of the penalty cost related to makespan over all the jobs and the total electricity cost for charging batteries of forklifts. Constraints (2)-(17) are related to the job scheduling and forklift assignments, whilst (18)-(29) are aimed at scheduling the battery changes and determining the optimal recharging cost strategies. Finally, constraints (30)-(38) specify the integrality conditions on the defined decision variables. The meaning of each constraint is detailed as follows.

Constraints (2) make sure that each job is assigned to one forklift only. Constraints (3) force the starting and completion times of job j by forklift m to zero in case job j is not assigned to forklift m . Constraints (4) guarantee that for each job the difference between the starting and the completion times is equal to the sum of the idling and processing times on the selected forklift. Constraints (5) ensure that each job j' is initiated later than the completion of its immediately preceding job j on any forklift. Constraints (6) make sure that each job j' has only one immediately preceding activity j on any forklift. Note that activity $j = 0$ identifies the initial setup of any forklift occurring at the beginning of the planning horizon. Constraints (7) make sure that each job j has only one immediately succeeding activity j' on any forklift. Note that job $j' = J + 1$ identifies the final setup of any forklift occurring at the end of operations. Constraints (8) and (9) ensures that each forklift is assigned to one initial and final setup activity only. Constraints (10) calculates the precedence relations between any activities. Constraints (11) and (12) determine the starting and completion time of jobs, respectively. Constraints (13) ensure that the completion time of each job is lower than or equal to the makespan. Constraint (14) calculates the total penalty cost related to the completion time over all the jobs.

Constraints (15) and (16) update the battery capacity through the execution of jobs. In particular, (15) initializes the battery capacity in forklifts in the jobs allocated at the beginning of the planning horizon, whilst (16) calculates the residual battery capacity by first order state transition between subsequent jobs. Constraints (17) update the residual battery capacity at the beginning of job j taking into account the eventual replacement with a fully-charged battery. Constraints (18) guarantees that the capacity of the battery in any forklift is enough to complete job j . Constraints (19) and (20) determine the starting and completion time of the battery charging processes, respectively. Constraints (21) force the starting and

completion times of the battery charging process related to job j to zero in case job j is not assigned to a battery replacement. Constraints (22) and (23) ensure the unicity of starting and completion instants for each battery charging process in the whole planning window. Constraints (24) calculate the time window when the charging could be executed. Constraints (25) and (26) determine the time slots when the energy is bought from the grid and used to charge the battery. Constraints (27) ensure that the number of available fully-charged batteries is non-negative in each time slot. Constraint (28) calculates the energy consumed in each time slot. Constraint (29) calculates the total energy cost related to the battery full charging over the whole time horizon.

Problem (1)-(38) is a non-linear integer program since two cross product terms $b_j \gamma_{jj}$, $z_j \beta_{jj}$, and $s_j z_j$ are present in (16), (17) and (26), and (19), respectively.

4. Numerical experiment

4.1. Setup of experiments

We consider a warehouse where $M = 2$ forklifts have to handle $J = 7$ independent jobs with the same due date. The planning horizon is composed by $T = 40$ time slots. Table 1 reports the parameters related to the jobs (i.e., processing duration in terms of time slots) and the initial state conditions for forklifts (i.e., setup completion time and state of charge of the on-board battery). Furthermore, Table 1 reports the parameters related to the batteries (minimum and maximum allowed state of charge and initial state of charge of the on-board battery for each forklift), normalized with respect to energy consumed per slot by the forklift. In particular, as indicated in last row of Table 1, we assume that in each forklift the battery is fully charged at the beginning of operations.

We further assume that the energy costs is time-dependent. In particular, we consider a time-of-use (TOU) pricing [25] where two different tariffs are applied over the planning horizon divided into five time frames. We assume that the on-peak electricity rate is two times the off-peak electricity rate. Figure 2 shows in detail the unitary energy cost per slot, normalized with respect to off-peak tariff.

As for the optimization parameters, we assume two different set of values for the weighting factors of the two objective function terms (i.e., makespan PC and energy cost for battery recharging EC), i.e., $\pi^I = \pi^{II} = 0.5$ (case a) and $\pi^I = 1, \pi^{II} = 0$ (case b). Hence, case a) corresponds to minimizing both the makespan and energy cost for battery recharging, whilst case b corresponds to minimizing only the makespan disregarding any energy cost savings. Finally, in order to equally compare the energy cost of the schedules computed in both cases, we impose that the final conditions are equal to the initial ones (i.e., each forklift is left with a fully-charged battery 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, letting the charging station to totally charge the lastly unloaded batteries.

The resulting scheduling problem (1)-(37) presents 113 integer and 1,309 binary variables, with 2,844 bounding

Description	Symbol	Value
Processing duration for each job	p_j ($\forall j = 1, \dots, J$)	[5,6,7,8,4,4,9]
Setup completion time slot for each forklift	c_{0m} ($\forall m = 1, \dots, M$)	[1,2]
Initial number of available fully-charged batteries	n_0	2
Penalty unitary cost	q	1
Fully-charged battery capacity	b_{max}	10
Minimum battery capacity	b_{min}	1
Initial state of charge of the on-board battery for each forklift	b_{0m} ($\forall m = 1, \dots, M$)	[10,10]

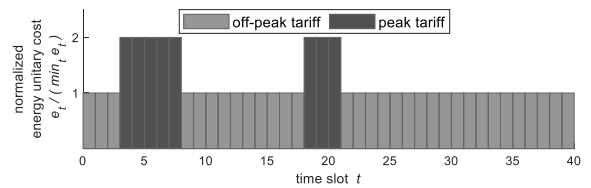


Fig. 2. Normalized energy unitary cost versus time.

constraints, 400 equality constraints, and 476 inequality constraints. Following the approach proposed by [26], a linearized version of the problem is implemented and solved in the MATLAB environment integrated with the SCIP (Solving Constraint Integer Programs) tool [27]. All the presented computations are executed on a PC equipped with a 4.0 GHz Intel Core i7 CPU and 16 GB RAM. The total computational runtime for all the simulations is about 250 seconds.

4.2. Results and discussion

We analyze the schedules obtained by applying the proposed method to the presented scenario, which are illustrated in Figs 3-4. In particular, Figures 3a and 3b show the Gantt chart of handled jobs and, for each forklift, discharging/replacement diagrams of batteries for both cases of analysis. It is apparent from Figs. 3a and 3b that the makespan is equal both in case a) and b) (as shown in the second row of Table 2), whilst the jobs are handled in accordance with distinct sequences. We also highlight that forklifts generally replace batteries at different time slots. Figures 4a and 4b 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 in the available charging station and ends when the battery is plugged-out. From Fig. 4a it is evident that in case a) the charging station is not switched-on over all the plugged-in time slots. For instance, in the first recharging cycle of the second charging station, the battery is plugged-in between time slots 6 and 14, but it is actually charged in the slot range [10-14] only). 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 Fig. 4b it is evident that in case b) the charging process is continuously active meanwhile batteries are plugged in the charging stations. Moreover, we

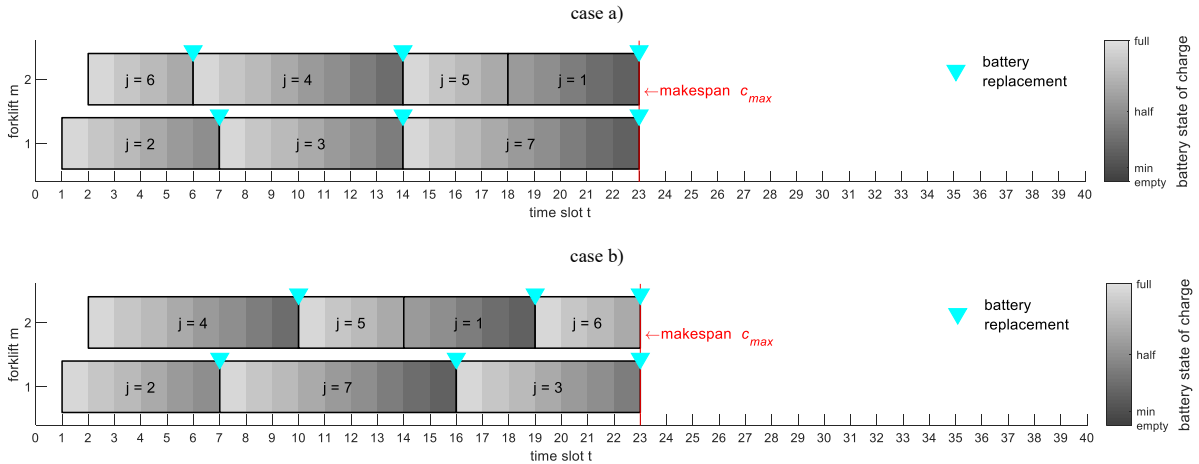


Fig. 3: Gantt chart of jobs and discharging/replacement diagrams of batteries on each forklift.

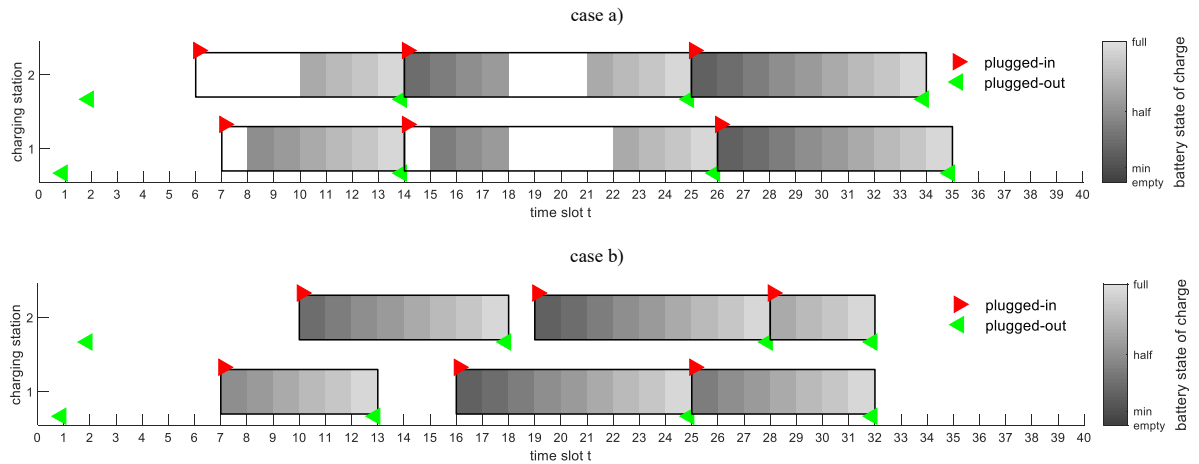


Fig. 4: Scheduling of recharging operations and charging diagram of batteries on each charging station.

remark that, in both case a) and b), the last recharging cycle corresponds to the charging process of batteries used by forklift to handle the last job of their operation sequence. 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 profile of the overall energy consumed over time by the charging stations are different in case a) and b), as highlighted in Figs. 5a and 5b. In particular, we note that the amount of energy acquired during on-peak time slots is greater in case b) than in case a) (where it is zero). As a result, the overall energy cost for the recharging operations is lower in case a) than in case b) (namely, 8.5% as shown in the last row of Table 2).

Finally, Figs. 6a and 6b 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 2). 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 b) than in case a).

5. Conclusion

Warehousing activities represent key components in many supply chains, and although different approaches were developed in the scientific literature with the aim of reducing the energy consumption of forklifts in material handling operations, many aspects are not yet deeply analyzed. In this context, the model developed in this manuscript allows to jointly evaluate the job scheduling and the energy consumption profile of MHE in picking processes (RQ1). The proposed model is a valid support for companies and warehouse managers in identifying the optimal battery-charging schedule of a fleet of electric mobile MHE under economic perspective (RQ2) in case of dynamic energy pricing.

Nevertheless, there are still substantial gaps in this work that require further investigation. There is the need to evaluate how the different independent variables, characterized by degree of uncertainty (e.g., readiness time of the job/s, battery charging capacity, charger efficiency, etc.) can affect the performance of the scheduling carried out by the model. Moreover, for future

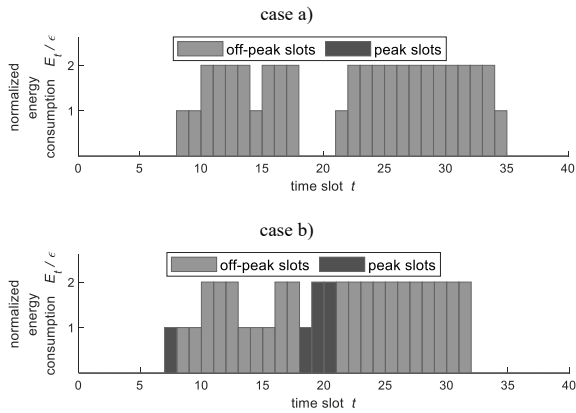


Fig. 5. Profile of normalized energy consumption.

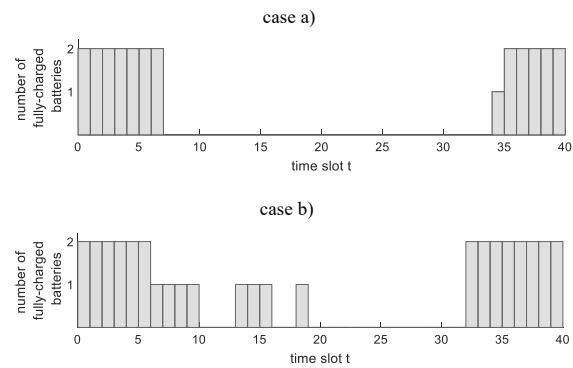


Fig. 6. Number of available fully-charged batteries.

Table 2: Comparison of analyzed cases

	case a)	case b)
Makespan: PC	23	23
Normalized energy cost: $EC/(\epsilon \text{ min}, e_t)$	43	47

development, additional details can be required (for instance the time for battery replacement is not considered here as well as all the jobs are assumed uninterrupted). Consistently with the improvement of the model, an assessment evaluation of the related computational complexity for more complex scenarios (i.e., greater number of jobs, forklifts, batteries, etc.) is required. Future research will also investigate the adoption of heuristic resolution approaches.

References

[1] Bartolini M, Bottani E, Grosse EH. Green warehousing: Systematic literature review and bibliometric analysis. *Journal of Cleaner Production* 2019, 226:242-258.

[2] Dhooma J, Baker P. An exploratory framework for energy conservation in existing warehouses. *International Journal of Logistics Research and Applications* 2012; 15(1):37-51.

[3] International Energy Agency, 2016. *International Energy Outlook*. Available from: <https://www.iea.org/> [accessed 2 September 2019]

[4] Piccinni G, Avitabile G, Coviello G, Talarico C. Analysis and Modeling of a Novel SDR-Based High-Precision Positioning System. In: 2015 Int. Conf. on Synthesis, Modeling, Analysis and Simulation Methods and Applications to Circuit Design (SMACD), 2018, p. 13-16.

[5] Piccinni G, Avitabile G, Coviello G. A novel distance measurement technique for indoor positioning systems based on Zadoff-Chu Sequences. In: 2017 15th IEEE International New Circuits and Systems Conference (NEWCAS), 2017, p. 337-340.

[6] Gattullo M, Evangelista A, Uva AE, Fiorentino M, Boccaccio A, Manghisi VM. Exploiting Augmented Reality to Enhance Piping and Instrumentation Diagrams for Information Retrieval Tasks in Industry 4.0 Maintenance. In: *Proceedings of the International Conference on Virtual Reality and Augmented Reality*. Springer, Cham, 2019, p. 170-180.

[7] Uva AE, Fiorentino M, Gattullo M, Colaprico M, De Ruvo MF, Marino F, Trotta GF, Manghisi VM, Boccaccio A, Bevilacqua V, Monno G. Design of a projective AR workbench for manual working stations, in *International Conference on Augmented Reality, Virtual Reality and Computer Graphics*. Springer, Cham, 2016. p. 358-367.

[8] Freis J, Vohlidka P, Gunthner WA. Low-Carbon Warehousing: Examining Impacts of Building and Intra-Logistics Design Options on Energy Demand and the CO2 Emissions of Logistics Centers. *Sustainability* 2016, 8, 448.

[9] Zhang Q, Grossmann IE. Enterprise-wide optimization for industrial demand side management: Fundamentals, advances, and perspectives. *Chemical Engineering Research and Design* 2016, 116:114-131.

[10] Moon JY, Park J. Smart production scheduling with time-dependent and machine-dependent electricity cost by considering distributed energy resources and energy storage. *International Journal of Production Research* 2014, 52(13):3922-3939.

[11] Bortolini M, Faccio M, Ferrari E, Gamberi M, Pilati F. Time and energy optimal unit-load assignment for automatic S/R warehouses. *International Journal of Production Economics* 2017, 190:133-145.

[12] Malaguti E, Nannicini G, Thomopulos D. Optimizing allocation in a warehouse network. *Electronic Notes in Discrete Mathematics* 2018, 64:195-204.

[13] Ghalekhondabi I, Masel DT. Storage allocation in a warehouse based on the forklifts fleet availability. *Journal of Algorithms & Computational Technology* 2018, 12(2):127-135.

[14] Ene S, Küçükoglu I, Aksoy A, Oztürk N. A genetic algorithm for minimizing energy consumption in warehouses. *Energy* 2016, 114:973-980.

[15] Boysen N, Fedtke S, Weidinger F. Optimizing automated sorting in warehouses: The minimum order spread sequencing problem. *European Journal of Operational Research* 2018, 270 (1):386-400.

[16] Boysen N., Briskorn D, Emde S. Parts-to-picker based order processing in a rack-moving mobile robots environment. *European Journal of Operational Research* 2017, 262:550-562.

[17] Minav TA, Laurila LIE, Immonen PA, Haapala ME, Pyrhonen JJ. Electric energy recovery system efficiency in a hydraulic forklift. In: *Proceedings of IEEE EUROCON*; 2009, p. 758-765.

[18] Minav TA, Laurila LIE, Pyrhonen J J. Analysis of electro-hydraulic lifting system's energy efficiency with direct electric drive pump control. *Automation in Construction* 2013, 30:144-150.

[19] Carli R, Dotoli M. Decentralized Control for Residential Energy Management of a Smart Users' Microgrid with Renewable Energy Exchange IEEE/CAA. *Journal of Automatica Sinica* 2019, 6(3):641-656.

[20] Finn P, Fitzpatrick C. Demand side management of industrial electricity consumption: promoting the use of renewable energy through real-time pricing. *Applied Energy* 2014, 113:11-21.

[21] Gellings CW. The concept of demand-side management for electric utilities. In: *Proceedings of the IEEE*; 1985, 73(10), p. 1468-1470.

[22] Paulus M, Borggrefe F. The potential of demand-side management in energy-intensive industries for electricity markets in Germany. *Applied Energy* 2011, 88(2):432-441.

[23] Ramin D, Spinelli S, Brusaferrri A. Demand-side management via optimal production scheduling in power-intensive industries: The case of metal casting process. *Applied Energy* 2018, 225:622-636.

[24] Zhao S, Ochoa MP, Tang L, Lotero I, Gopalakrishnan A, Grossmann IE. Novel Formulation for Optimal Schedule with Demand Side Management in Multiproduct Air Separation Processes. *Industrial & Engineering Chemistry Research* 2019, 58(8):3104-3117.

[25] Çelebi E, Fuller JD. Time-of-use pricing in electricity markets under different market structures. *IEEE Transactions on Power Systems* 2012, 27(3):1170-1181.

[26] Glover F. Improved linear integer programming formulations of nonlinear integer problems. *Management Science* 1975, 22 (4):455-460.

[27] Achterberg, T. SCIP: solving constraint integer programs *Mathematical Programming Computation* 2009, 1:1-41