An optimization approach and a heuristic procedure to schedule battery charging processes for stackers of palletized cargo

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Abstract

This paper proposes an approach to develop schedules for charging batteries in a battery center. This problem arises in warehouses and logistics centers that attempt to provide uninterrupted operations with battery powered machinery such as stackers. These operations often require recharging batteries on location, a process that involves two decisions: determining charging start-times and assigning batteries to chargers. Prices of grid-provided electric energy vary by hour of the day and can be almost negligible for energy available from photovoltaic solar collectors. Thus, efficient schedules should recharge batteries during time intervals with low tariffs while minimizing the time batteries spend in queue waiting for an available charger. In this situation, batteries arrive at the battery center during the operation. The model assumes that the counts of arriving batteries in time bands are known. The objective is to determine a charging schedule that minimizes a weighted sum of the costs of energy and delays. We develop a MIP model that incorporates the main features of the battery charging process. Unfortunately, computation times to solve these MIPs are too long to be practical. To overcome this limitation, we develop a constructive heuristic that finds a feasible solution in a matter of seconds, even for large-sized instances, with a relatively low GAP of 9.67%.

Keywords: Warehouse operations, Energy efficiency, Scheduling, MIP modeling, Greedy heuristic.

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1. Introduction

The management of logistics centers is becoming increasingly challenging. In addition to tighter customer requirements (Kim, 2018; Varas et al., 2018) and stricter environmental laws (Halat and Hafezalkotob, 2019; Basso et al., 2019a), companies are facing increasing pressure to limit their adverse social effects. In Chile, where the problem we address emerged, the construction of Walmart's largest logistics investment in Latin America during 2018 – a distribution center – was postponed for several months due to opposition from the local community. Making logistics processes more sustainable is therefore crucial to compete in this industry.

In particular, environmental and social concerns lead companies to shift to the use of zero-emission electric vehicles (EVs) for their logistics and transportation processes. The use of these vehicles allows companies to reduce their carbon footprint and to access an increasing number of government subsidies that reduce acquisition costs (Juan et al., 2016). Furthermore, the use of renewable energy sources, such as solar, may contribute to reduce even further the environmental impact of these vehicles and to reduce the charging cost (Saber and Venayagamoorthy, 2011). Nevertheless, logistics managers must also address several other economic aspects, especially as they strive to reduce operational costs as much as possible in order to stay profitable (Yener and Yazgan, 2019).

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Compared to diesel vehicles, the EVs have the disadvantage of requiring a long recharge time. Thus, even in a context where batteries can be removed from vehicles for the recharging process (swapping batteries), supporting the battery center (BC) operations is critical for both reducing the costs incurred for charging the batteries and for diminishing the time batteries spend in queue waiting for a charger, which reduce the service level. One way to increase the efficiency at BCs is to improve charging schedules. Addressing the battery charge-scheduling problem is therefore crucial in this operational environment.

This paper studies BC operations in warehouses that use electric stackers with battery swapping for moving pallets or boxes. Tackling the scheduling of the battery charge for this problem proves quite complex. It involves assigning batteries to specific chargers and determining charging start-times, considering both periods where inexpensive but limited photovoltaic solar energy is available and periods of varying price of grid-available electric energy. In this sense, the charging process can be seen as a job scheduling problem which is known to be hard to solve. Moreover, batteries present irregular charging profiles which require tracking their specific energy requirements during any period of charge. Irregular charging profiles make the problem much harder to solve, so experience-based developed schedules may exhibit quite poor performances. Thus, the research question is to develop computationally-efficient and low-cost schedules for charging batteries. We use operations research tools to tackle this problem.

The contribution of this paper is two-fold. First, we develop a novel mixed integer programming model to schedule battery charging processes for stackers of palletized cargo. To the best of our knowledge, this is the first effort in the relevant literature. Second, solving the proposed mixed-integer programming formulation is sufficiently complex so that, for real-size instances, state-of-the-art solvers such as CPLEX cannot find any feasible solution in reasonably short computing time. To overcome this limitation, we develop a greedy algorithm that exploits the structure of our mixed integer programming formulation. Numerical experiments illustrate the value of our heuristic approach.

The rest of this paper is organized as follows. Section 2 reviews relevant literature. Section 3 describes BC operations with detail. Section 4 presents the formulation of the battery charge-scheduling problem. Section 5 describes the greedy heuristic algorithm used to find feasible solutions. Section 6 closes with concluding remarks and with a description of lines for future research.

2. Literature review

A recent but well-studied line of research analyzes battery-charging problems for EVs for private and public transportation, rather than for freight transportation in warehouses, the subject of our paper. Indeed, some authors have proposed scheduling and management models for charging or discharging EVs (Honarmand et al., 2014; Álvaro and Fraile-Ardanuy, 2015; Sassi and Oulamara, 2017; Kabir and Suzuki, 2018b). These models usually use linear programming formulations and heuristic approaches, as we do, to determine the optimal arrival time of EVs to charging stations. These optimal times depend on variables such as the state of charge (SOC) and the distance from the EV to the nearest station. In contrast, in the problem of our environment, these times are known parameters, and the EVs arrive at the BC with their batteries fully discharged. In other words, we know exactly the time that each EV arrives at the charging station. These methodologies, as well as ours, enable managers to evaluate optimal infrastructure requirements, e.g., the optimal number of chargers. A separate line of research has studied

EV routing problems (Hung and Michailidis, 2015; Keskin and Çatay, 2018). In contexts where battery capacity limits EVs driving range, they may need to reach charging stations to complete its route. In such contexts, in contrast to ours, the challenge is to determine a route for the EV rather than schedule the chargers. Along with this line, Yang et al. (2017) propose an integer linear programming model to allocate battery chargers for electric taxis.

As we do here, Zou et al. (2018) propose operations research approaches to manage battery charging processes in warehouses. Their objective, nevertheless, is to evaluate the performance of a robotic mobile fulfillment system using stochastic models and simulation. Kabir and Suzuki (2018a) explore how different routing techniques for battery management of Automated Guided Vehicles (AGVs) can affect the performance of a system. These authors use a discrete event simulation model to assess the productivity of four heuristics. Nowadays, most of the AGVs have automatic controls. Nevertheless, in the context of this paper, operators drive the EVs. Some papers have proposed operations research economic models to determine the AGVs fleet size (Sinriech and Tanchoco, 1992; Rajotia et al., 1998; Choobineh et al., 2012). For a survey of scheduling and routing problems for AGVs, we refer the reader to Qiu et al. (2002).

Global climate change motivates companies to prefer environmentally friendly energy sources in their operations (Wang and Li, 2017). Besides, electricity is a significant portion of operational costs in most manufacturing systems. Countries have varying electricity tariffs, and companies increasingly use these differences to reduce electricity costs. In a more general setting than ours, Mikhaylidi et al. (2015) analyze a job scheduling problem under time-varying prices for electricity. The authors propose a dynamic programming strategy to find optimal schedules. Similarly, Moon and Park (2014) minimize the total production cost for a flexible job-shop scheduling problem with time-dependent and machine-dependent electricity cost. Cheng et al. (2017) analyze a single-machine batch scheduling problem under time-of-use tariffs. We refer the reader to Biel and Glock (2016) for a systematic literature review of decision support models for energy-efficient production planning.

In the situation we model, each battery that arrives at the BC is assigned to a number of equal parallel chargers. Thus, our battery charge-scheduling problem is a special case of an *identical parallel machine shop problem with no setup times under a weighted total tardiness/completion time plus weighted flow time criteria*. According to the taxonomy in Graham et al. (1979), and with the notation of Allahverdi (2015), the battery charging problem reduces to an $P/ST_{si}/(\sum w_jT_j + \sum w_jF_j)$ scheduling problem. We refer the reader to Allahverdi et al. (1999), Cheng et al. (2000), Allahverdi et al. (2008) and Allahverdi (2015) for complete reviews on these kind of problems.

Several industrial problems can be modeled as scheduling jobs in parallel machines. Examples, are operations of the import area at cross-dock centers (Li et al., 2004); the assembly of high-value electronic products to distribute by air transportation (Li et al., 2008); the operation of a wire-bonding workstation in integrated-circuit packaging manufacturing (Yang, 2009); the operation of the pre-heat treatment stage in an automobile gear manufacturing process (Gokhale and Mathirajan, 2012); the management of production lines that produce knitted fabric for mattresses (Kerkhove and Vanhoucke, 2014); the loading and unloading operations in a multi stations transshipment terminal (Bazgosha et al., 2017); the wine bottling process management (Basso and Varas, 2017; Basso et al., 2019b) and the management of energy-efficiency nodes in servers for processing large-scale data applications (Shao et al., 2018). All these problems may be viewed as generalizations of the classic parallel machine scheduling problem, which is known to be NP-hard (Ho and Chang, 1995). Therefore, for problems of moderate or industrial size, the general practice is to find an adequate heuristic solution instead of an optimal solution (Yang, 2009). We tackle this issue in Section 5, with a greedy heuristic algorithm.

Before presenting the mathematical programming approach, Section 3 first describes further the operations at the BC to expose better and to explain in clear terms the complexity of the battery charge-scheduling problem.

3. Problem description

This research emerged in the context of a technology transfer cooperation between our research group and Royal America[1], a Chilean company that provides its clients with services of EVs and management of BCs, among others. Figure 1 depicts the charging process at the logistics center of a client of Royal America.

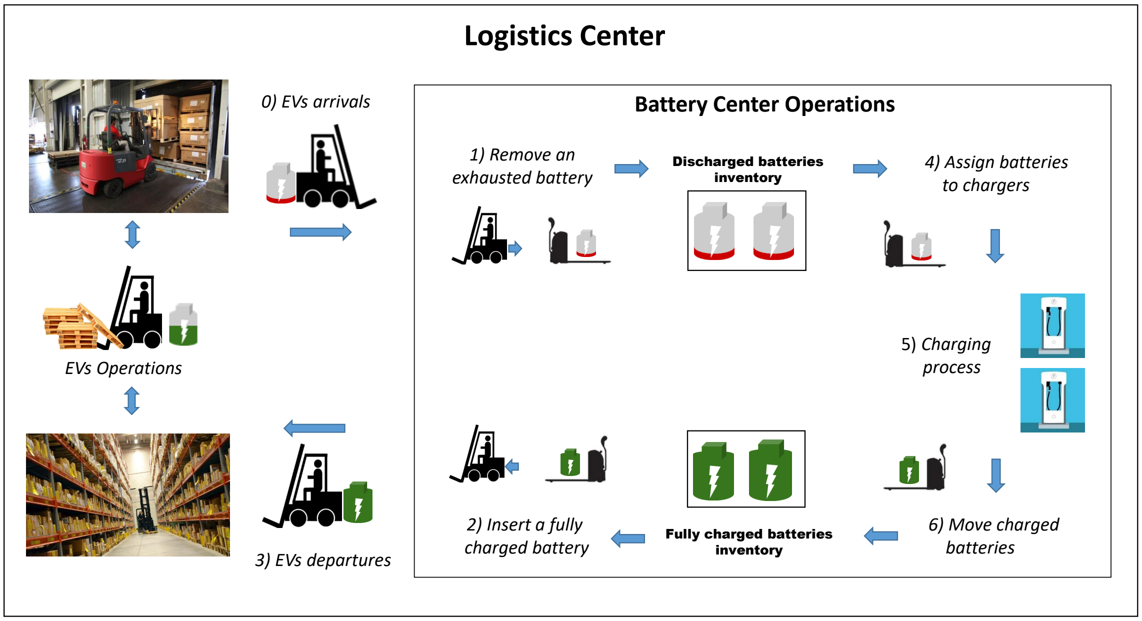

Figure 1: Scheme of the battery management operation at a BC

The dynamic of this process is as follows. When an EV exhausts the charge of its battery, the EV driver takes it to the BC (step 0) where a BC operator removes this battery from the EV and places it to the discharged batteries inventory (step 1). Then, the BC operator inserts a fully-charged battery, if available, to this same EV (step 2) which returns immediately to work (step 3). The battery swapping operation takes just a few minutes; hence we assume this time is negligible in our modeling approach. Nevertheless, if no charged batteries are available at that moment, the EV waits for one outside the BC. These delays are detrimental to the logistics center operations, which we incorporate as a cost in the objective function in our model (Subsection 4.5).

Next, the BC operator assigns the discharged battery to an available charger (step 4), if available, and the charging process starts (step 5). When the charge is complete, the BC operator places the charged battery in the fully charged batteries inventory (step 6).

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[1] http://royalamerica.com/cl/home

According to the managers we worked with, from the time a battery arrives at the BC, it remains there for at least eight hours, a time that includes charging (six hours) and resting (at least two hours). Resting extends the lives of the batteries.

The demand process is modeled as a sequence of arrival counts of requests for fully-charged batteries during short time bands (TB). In our context, the typical operation shift is eight hours long, while the TBs are one hour long. The input for the model is a record of requests in earlier but recent operation periods of the same duration. We call such a record a *profile of requests* for charged batteries for the planning horizon. This profile may be chosen to match the characteristics of the planning horizon. For instance, if the planning horizon is the shift from 8am to 4pm next Thursday, one may choose the profile of the 8am to 4pm shift from last Thursday. If the requests are roughly stationary during the operation, then one may use the most recent eight-hour-long profile of requests to plan the operation for the next eight-hour period.

For concreteness, our description of the problem uses EVs, but are immaterial to formalizing the battery charge-scheduling problem. The input that the charge-scheduling model uses are the arrival counts of requests for fully-charged batteries (step 0). In other words, for scheduling purposes, only the arrival counts to the BC in each TB are needed. The operations of the EVs outside the BC (step 3), therefore, are out of the scope of this paper.

Each battery that arrives at the BC for recharging is connected to a charger appropriate to the battery type (step 4). The design of the BC stipulates that there are enough batteries for each EV. Thus, the number of batteries is not a source of interruption of operations. On the other hand, the chargers are a possible source of disruption if they are insufficient to match the battery types that arrive for charging. Moreover, as Figure 2 shows, batteries have irregular charging profiles, thus scheduling requires tracking their specific energy requirements throughout the charging period. This feature makes the problem a one much harder to address.

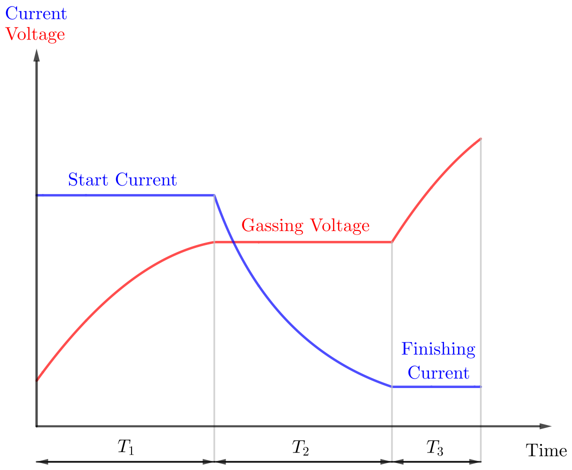


Figure 2: Battery charging profile.

A distinct feature of the situation we model is that each EV in the serving fleet uses a battery of a specific type. The battery types are not exchangeable, that is, if an EV uses a given type of battery, this EV does not admit another type of battery (step 2). Voltage and

size define battery types. Thus, the request process for charged batteries is more complex than in standard problems of EV charging: here the BC must meet each request for a battery with one fully-charged of the same type.

On the other hand, charging stations can admit more than one type of battery, but only one at a time, since special connectors are required to provide the appropriate levels of current and voltage. This feature is crucial: if it were not the case, that is, if charging stations would admit only one type of battery, then the problem could be separated for each battery type. Therefore, the sharing of charging stations among batteries of different types may help reduce costs, but it adds complexity to the problem.

Charging stations can provide the electric energy to charge the batteries that the fleet of EV requires using standard electrical grid-supplied energy in combination with small photovoltaic solar energy (step 5). The company we worked with does not use its batteries to store any excess power for nighttime use. Therefore, the use of solar energy is restricted to a few hours during daytime. Furthermore, the availability of solar energy is minimal, given the current company's energy infrastructure and only a subset of the chargers can provide solar energy. Thus, not every charging request can be satisfied with this type of energy.

Intra-day tariff differentials open opportunities to improve the efficiency of energy consuming operations. Indeed, short term storage in batteries allows operators to bypass hours of expensive power for recharging. Our research gears precisely to determine optimal schedules for recharging batteries for work-shifts in operating environments where grid energy tariffs very during the day, when solar energy is available during hours of available solar radiation, and where delays to provide a charged battery to a machine have significant costs.

Overall, the battery charge-scheduling problem can be stated as follows: assign batteries to specific chargers and determine charging start-times, considering both periods where inexpensive but limited photovoltaic solar energy is available and periods of varying price of grid-available electric energy. In this context, improving the charging process could reduce the charging costs, especially when energy prices vary, and reduce the time batteries spend in the queue waiting for a charger, which worsens the level of service.

Thus, the charging process can be seen as a job-scheduling problem that is known to be hard to solve. We believe that the use of advanced analytical methods improves decision making in this context rather than BC operators experience. In the next section, we propose a mixed integer programming formulation to tackle this problem.

4. The Mixed Integer Programming Model

This section describes a MIP formulation for the battery charge-scheduling problem. Section 4.1 states the assumptions; Section 4.2 describes the sets and parameters of the model; Section 4.3 defines the decision variables; Section 4.4 establishes the constraints; Section 4.5 establishes the objective function and discusses some modeling issues. Finally, Section 4.6 illustrates our approach with an example.

4.1. Assumptions

Our modeling approach uses the following assumptions:

- The *profile of requests* is known and without uncertainty.
- There are several types of batteries.
- There are two types of energy supply, namely, grid and photovoltaic solar energy.
- The photovoltaic solar energy has output limits that depend on the hour of the day.
- The grid energy has unlimited output.
- Only a subset of the chargers can provide solar energy.
- Charging and resting times depend only on the battery type.
- Setup times are negligible.

The next subsection describes the data the model uses. This data characterizes the operations, the requests, and the resources to manage the BC.

4.2. Parameters

The parameters the model are:

$B \in \mathbb{N}$: Number of battery types.
$R \in \mathbb{N}$: Number of charger types.
$M \in \mathbb{N}$: Number of TBs, i.e. the planning horizon.
$N_b \in \mathbb{N}$: Number of batteries of type $b \in \{1, \ldots, B\}$.
$K_b \in \mathbb{N}$: Number of fully-charged batteries of type $b \in \{1, \ldots, B\}$ required throughout the planning horizon.
$I_b \in \mathbb{N}$: TBs needed to fully-charge a battery of type $b \in \{1, \ldots, B\}$.
$L_{bn} \in \mathbb{N}$: Lower bound for the initial charging TB of the battery $n \in \{1, \ldots, N_b\}$ of the type $b \in \{1, \ldots, B\}$.
$RS_b \in \mathbb{N}$: Resting time (in number of TBs) for a battery of type $b \in \{1, \ldots, B\}$.
$D_{bk} \in \mathbb{N}$: TB where the battery $k \in \{1, \ldots, K_b\}$ of type $b \in \{1, \ldots, B\}$ is required to be available fully-charged.
$CH_{br} \in \{0, 1\}$: It takes value 1 if a battery of type $b \in \{1, \ldots, B\}$ can be charged by the charger type $r \in \{1, \ldots, R\}$.
$SOL_r \in \{0, 1\}$: It takes value 1 if the charger type $r \in \{1, \ldots, R\}$ can provide solar energy.
$DISCH_{bn} \in \{0, 1\}$: It takes value 1 if the battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$ enters the BC discharged. It takes 0 for batteries in stock and fully-charged.
$U_{bn} \in \{0, 1\}$: It takes value 1 if the battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$ will be used to fulfill a request. It takes 0 for the last $N_b - K_b$ batteries.
$CS_m \geq 0$: Solar energy cost during TB $m \in \{1, \ldots, M\}$ [USD/kWh].
$CG_m \geq 0$: Grid energy cost during TB $m \in \{1, \ldots, M\}$ [USD/kWh].
$GS_m \geq 0$: Solar energy availability during TB $m \in \{1, \ldots, M\}$ [kWh].
$F_{bi} \geq 0$: Energy requirement of a battery of type $b \in \{1, \ldots, B\}$ in the TB $i \in \{1, \ldots, I_b\}$ of charge [kWh].
$W_b \geq 0$: Monetary value for delays of battery type $b \in \{1, \ldots, B\}$ [USD/TB].

4.3. Variables

The decision variables in the model are:

$g_{bn} \in \mathbb{N}$: Initial charging TB of the battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$.

$s_{bnm} \geq 0$: Solar energy used for charging the battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$ in the TB $m \in \{1, \ldots, M\}$ [kWh].

$t_{bnm} \geq 0$: Grid energy used for charging the battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$ in the TB $m \in \{1, \ldots, M\}$ [kWh].

$u_{bnmi} \in \{0, 1\}$: It takes value 1 if the battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$ is in its i-th $\in \{1, \ldots, I_b\}$ TB of charge at the m-th $\in \{1, \ldots, M\}$ TB of the planning horizon.

$x_{bnr} \in \{0, 1\}$: It takes value 1 if the battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$ is charged in a charger of type $r \in \{1, \ldots, R\}$.

$y_{bnb'n'} \in \{0, 1\}$: It takes value 1 if the battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$ is charged after the battery $n' \in \{1, \ldots, N_{b'}\}$ of the type $b' \in \{1, \ldots, B\}$ in the same charger.

$\varepsilon_{bk} \in \mathbb{N}_0$: Tardiness (in number of TBs) of the requested battery $k \in \{1, \ldots, K_b\}$ of the type $b \in \{1, \ldots, B\}$.

The decisions in this problem are the assignment of batteries to specific chargers $(x_{bn}, y_{bnb'n'})$ and the management of the charging process within the charger $(g_{bn}, s_{bnm}, t_{bnm}, u_{bnmi}, \varepsilon_{bk})$.

4.4. Constraints

The constraints are as follows:

$$s_{bnm} + t_{bnm} = U_{bn} \cdot DISCH_{bn} \cdot \left(\sum_{i=1}^{I_b} u_{bnmi} \cdot F_{bi} \right) \qquad \forall b, n, m \tag{1}$$

$$\sum_{b \in B} \sum_{n=1}^{N_b} s_{bnm} \leq GS_m \qquad \forall m \tag{2}$$

$$\sum_{m=1}^{M} u_{bnmi} = 1 \qquad \forall b, n, i \tag{3}$$

$$(i-1) + g_{bn} = \sum_{m=1}^{M} m \cdot u_{bnmi} \qquad \forall b, n, i \tag{4}$$

$$L_{bn} \leq g_{bn} \qquad \forall b, n \tag{5}$$

$$g_{bn} \leq g_{bn+1} \qquad \forall b, n \tag{6}$$

$$U_{bn} \cdot DISCH_{bk} \left(g_{bk} + I_b + RS_b \right) - D_{bk} \leq \varepsilon_{bk} \qquad \forall b, k \tag{7}$$

$$x_{bnr} \leq CH_{br} \qquad \forall b, n, r \tag{8}$$

$$\sum_{r=1}^{R} x_{bnr} = U_{bn} \cdot DISCH_{bn} \qquad \forall b, n \tag{9}$$

$$\sum_{m=1}^{M} s_{bnm} \leq \left(\sum_{i=1}^{I_b} F_{bi} \right) \left(\sum_{r=1}^{R} x_{bnr} \cdot SOL_r \right) \qquad \forall b, n \tag{10}$$

$$y_{bnb'n'} \leq 1 + \frac{g_{bn} - g_{b'n'}}{M+1} \qquad \forall n, n', b, b' \tag{11}$$

$$y_{bnb'n'} \leq 1 - x_{bnr} + x_{b'n'r} \qquad \forall n, n', b, b', r \tag{12}$$

$$y_{bnb'n'} \geq x_{bnr} + x_{b'n'r} - 2 + \frac{g_{bn} - g_{b'n'}}{M+1} \qquad \forall n, n', b, b', r \tag{13}$$

$$1 \geq x_{bnr} + x_{b'n'r} - y_{bnb'n'} - y_{b'n'bn} \qquad \forall n, n', b, b', r \tag{14}$$

$$g_{b'n'} + I_{b'} \leq 2M(1 - y_{bnb'n'}) + g_{bn} \qquad \forall n, n', b, b' \tag{15}$$

Constraint (1) ensures that the energy requirement is satisfied during the charging process. Constraint (2) incorporates an upper bound on solar energy use. Constraint (3) establishes that each TB of charge is within the planning horizon once. Constraint (4) relates the initial charging TB with the following charging TBs. Note that Constraints (3)–(4) force u_{bnmi} to take value 1 when $m = g_{bn} + (i-1)$, that is, when the battery is in i-th TB of its charge. Constraint (5) gives a lower bound for the initial charging TB. Constraint (6) imposes the logical ordering between the initial charging TBs. Constraint (7) defines the tardiness of a request as the positive part of the difference between the availability time and its deadline. We include the variables ε_{bk} in the objective function to incorporate the cost of late battery deliveries. Constraint (8) ensures that the model assigns each battery only to an appropriate charger. Constraint (9) establishes that only discharged batteries are assigned to chargers. Constraint (10) establishes that a battery could be charged with solar energy only if the charger assigned is adequate to this energy source. Constraints (11)–(14) force $y_{bnb'n'}$ to take value 1 if and only if a battery nb is charged after a battery $n'b'$

in the same charger. Finally, (15) is a critical constraint. It defines a proper ordering for each charger that prevents overlapping between charging times in the same charger.

4.5. The objective function

The objective function aims for reducing both the energy cost and the aggregate delay to fulfill battery requests. The mathematical expression is :

$$\min \sum_{b=1}^{B} \sum_{n=1}^{N_b} \sum_{m=1}^{M} (CS_m \cdot s_{bnm} + CG_m \cdot t_{bnm}) + \sum_{b=1}^{B} W_b \sum_{k=1}^{K_b} \varepsilon_{bk}$$

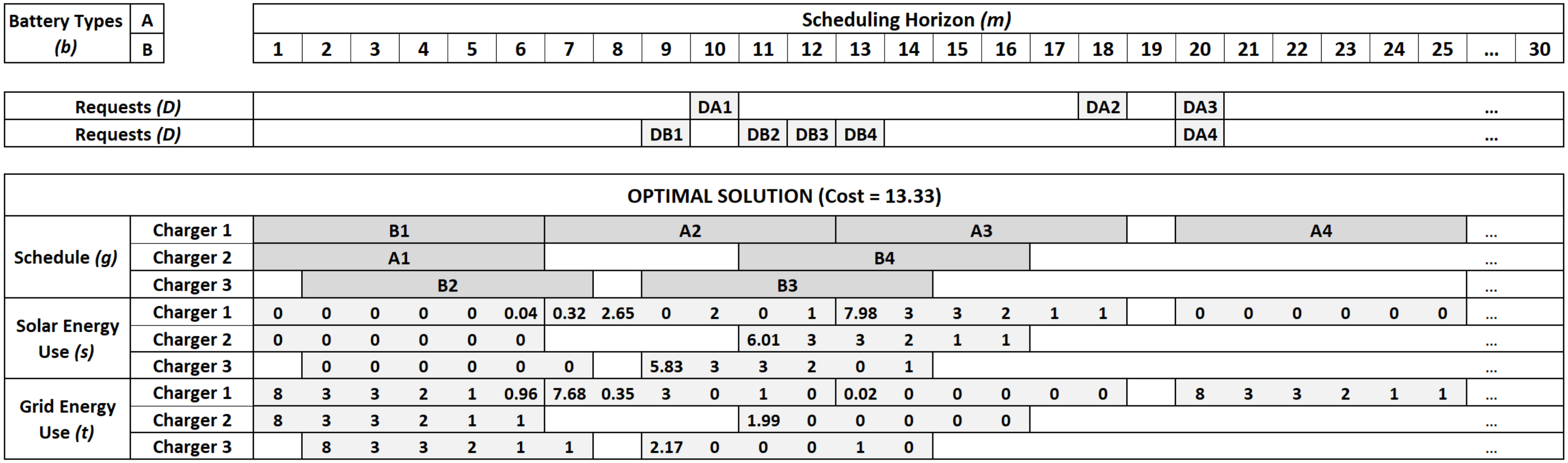
The first term represents the charging cost of grid and solar energy. The second term represents the monetary value of the delays. In practice, although hard to quantify, this last term may be interpreted as the opportunity cost of an interruption in the EVs services.

4.6. An illustrative example

To illustrate the application of our MIP approach, this section uses the above formulation and a synthetic instance with two battery types, three charger types, and eight requests (see Appendix A). We code the model in AMPL and solve the resulting problem with CPLEX 12.8.0.0 on a PC with an Intel(R) Core(TM) i7-5700HQ CPU @ 2.20Ghz processor and 12Gb RAM.

In this instance, the MIP model generates a problem with 2016 variables (1,520 binary, 16 integers and 480 continuous) and 1,156 constraints. CPLEX solves this problem to optimality in less than 2 seconds, with an optimal value of 13.33. Figure 3 reports the optimal solution.

Note that any feasible solution of this problem can be straightforwardly coded in a spreadsheet considering the values of g_{bn}, x_{bnr}, s_{bnm} and t_{bnm} $(\forall b, n, m, r)$. Plots such as Figure 3, allow managers to validate the output of this model is indeed feasible by checking the fulfillment of the constraints. For instance, a manager can check that the charging intervals of two batteries do not overlap in the same charger. These checks increase the confidence in the model solutions.



Battery Types *(b)*	
	A
	B

		Scheduling Horizon *(m)*																									
		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	...	30
Requests *(D)*											DA1								DA2		DA3						...	
Requests *(D)*										DB1		DB2	DB3	DB4							DA4						...	

OPTIMAL SOLUTION (Cost = 13.33)																											
Schedule *(g)*	Charger 1	B1						A2						A3							A4						...
	Charger 2	A1										B4															...
	Charger 3		B2							B3																	...
Solar Energy Use *(s)*	Charger 1	0	0	0	0	0	0.04	0.32	2.65	0	2	0	1	7.98	3	3	2	1	1		0	0	0	0	0	0	...
	Charger 2	0	0	0	0	0	0					6.01	3	3	2	1	1										...
	Charger 3		0	0	0	0	0	0		5.83	3	3	2	0	1												...
Grid Energy Use *(t)*	Charger 1	8	3	3	2	1	0.96	7.68	0.35	3	0	1	0	0.02	0	0	0	0	0		8	3	3	2	1	1	...
	Charger 2	8	3	3	2	1	1					1.99	0	0	0	0	0										...
	Charger 3		8	3	3	2	1	1		2.17	0	0	0	1	0												...

Figure 3: MIP optimal solution for the illustrative example.

5. A Greedy Heuristic Algorithm

This section proposes a greedy heuristic algorithm for the battery charge-scheduling problem that can be used with industrial size instances in reasonable computing times. Section 5.1 reports computational results that support the development of a constructive heuristic; Section 5.2 describes our greedy procedure; Section 5.3 assess the effectiveness of the greedy algorithm. Finally, Section 5.4 analyzes the performance of the greedy solutions.

5.1. Solving larger size instances

We solve MIP formulations for thirty-six synthetic test instances to analyze the behavior of the model under several request profiles. These instances differ in the number of battery changes, ranging from 6 to 100. To assess the impact of the number of battery types in the complexity of the problem, we consider three cases: 1, 5 and 10 battery types. Table 1 reports the computing time (CT) to obtain the first feasible solution (FS), the optimal solution (OS), and their corresponding objective function values (OV).

Battery Types	Requests	FS OV	GAP	FS CT (s)	OS OV	OS CT (s)
1	6	8.56	0.00%	<1	8.56	<1
1	8	25.38	6.59%	<1	23.71	1.59
1	10	29.21	9.35%	1.31	26.48	2.17
1	12	39.84	14.32%	1.77	34.13	8.27
1	15	73.26	20.06%	2.15	58.56	166.60
1	20	95.74	21.73%	3.44	74.94	18,365
1	25	121.16	-	7.70	-	>86,400
1	30	117.18	-	14.45	-	>86,400
1	40	190.85	-	40.56	-	>86,400
1	50	468.52	-	104.25	-	>86,400
1	75	662.20	-	2077.99	-	>86,400
1	100	-	-	>86,400	-	>86,400
5	6	10.29	0.00%	<1	10.29	<1
5	8	15.97	11.28%	<1	14.16	1.20
5	10	53.23	27.81%	1.21	38.43	10.71
5	12	68.57	27.69%	1.65	49.58	63.23
5	15	85.32	24.82%	2.21	64.14	26,336
5	20	98.06	-	9.94	-	>86,400
5	25	135.03	-	25.38	-	>86,400
5	30	178.50	-	67.56	-	>86,400
5	40	276.31	-	4417.95	-	>86,400
5	50	-	-	>86,400	-	>86,400
5	75	-	-	>86,400	-	>86,400
5	100	-	-	>86,400	-	>86,400
10	6	12.42	0.00%	<1	12.42	<1
10	8	32.55	17.42%	<1	26.88	1.78
10	10	62.21	29.85%	1.06	43.64	7.00
10	12	68.71	20.99%	1.12	54.28	24.09
10	15	120.50	-	1.48	-	>86,400
10	20	111.11	-	4.32	-	>86,400
10	25	168.87	-	7.97	-	>86,400
10	30	223.89	-	12.63	-	>86,400
10	40	261.98	-	484.36	-	>86,400
10	50	-	-	>86,400	-	>86,400
10	75	-	-	>86,400	-	>86,400
10	100	-	-	>86,400	-	>86,400

Table 1: MIP results for 36 test instances.

These results show that using a state-of-the-art solver to find a feasible solution is useful for small instances only. In particular, the MIP solver takes almost 35 minutes to find a feasible solution with an instance of 75 requests for a single battery type and does not find a feasible solution in 24 hours with 5 or 10 battery types. This last represents a severe limitation since in actual operations one may observe at least 100 battery changes in an 8-hour shift as we did observe in operations at Royal America. In such cases, CPLEX is unable to find a feasible solution even after running a full day for any number of battery types. Therefore, this approach is impractical to develop charging schedules in an operating environment such as in Royal America. Those long-running times motivate the development of efficient heuristic approaches to help BCs to improve their efficiency.

5.2. A constructive algorithm

This section proposes a constructive heuristic based on minimum cost criteria. This heuristic uses the following variables:

$r_{bn} \in \{1, ..., R\}$: Charger associated to the battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$.

$g_{bn} \in \{1, ..., M\}$: Initial charging TB of the battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$.

$z_{rm} \in \{0, 1\}$: It takes value 1 if the charger type $r \in \{1, \ldots, R\}$ is used duringTB $m \in \{1, \ldots, M\}$.

$S_m \geq 0$: Total use of solar energy during TB $m \in \{1, \ldots, M\}$

Furthermore, consider the following set which represents all possible schedules:

$$F = \{1, ..., R\}^{|B| \cdot |N_B|} \times \{1, ..., M\}^{|B| \cdot |N_B|}$$

To develop a feasible charging schedule, we need to define for each pair (b, n) a charger at which a battery will be charged (r_{bn}) and the first charging TB (g_{bn}). The rationale of our greedy heuristic is to assign a battery to a charger with the lowest charging cost. For this assignment, we consider an algorithm (Algorithm 1) that computes, given the current configuration characterized by the use of chargers, z, and the use of solar energy, S, the minimum cost of charging the battery (b, n) with charger r, starting in TB m. Two scenarios may arise in this case:

1. **If charger r is in use under the current configuration during any of the TBs $\{m, \ldots, m + I_b - 1\}$, then charging of the battery (b, n) cannot start in the TB m in this charger. This constraint stems from the fact that one should not interrupt the charging process of any battery.**
2. **In any other case, we assume that all the residual solar energy will be used. The rationale is that solar energy is considerably cheaper than grid energy. Therefore, for any battery (b, n), the cheapest way to add it to the current configuration is to use as much solar energy as possible, defined as the minimum between the available solar energy, $GS - S$, and the requirement of energy of the battery, F, as long as charger r can make use of solar energy ($SOL_r = 1$).**

Next, we describe the greedy algorithm (Algorithm 2). Starting with an empty schedule, the algorithm orders the batteries by their relative importance. For each battery, the algorithm evaluates the cost of each possible configuration (r_{bn}, g_{bn}) , as defined by Algorithm 1. Thus, this algorithm minimizes the cost and delays of the batteries most important to the operation first, while using all available solar energy.

The pseudo-code for the minimum cost function (Algorithm 1) and the greedy heuristic (Algorithm 2) follows.

Algorithm 1 Minimum Cost Function

```
Input: $b, n, m, r, z, S$
if $\sum_{k=m}^{m+I_b-1} z_{rk} \geq 1$ then                          ▷ Charger is in use.
    Return $\infty$
else                                                   ▷ We use all solar energy available.
    Return $\sum_{k=m}^{m+I_b-1} CS_k \cdot SOL_r \cdot \min\{F_{b,(k-m+1)}, GS_k - S_k\}$
           $+CG_k \cdot (F_{b,(k-m+1)} - SOL_r \cdot \min\{F_{b,(k-m+1)}, GS_k - S_k\})$
           $+W_{bn} \max\{0, m + I_b - 1 - D_{bn}\}$
end if
```

Algorithm 2 Greedy Heuristic

```
$z, S \leftarrow 0$
TotalCost $\leftarrow 0$
for $b \in 1 \ldots B$ ordered by $W$ do
    for $n \in 1 \ldots N_b$ do
        cost$_{bn} \leftarrow \infty$                ▷ Initialize cost of charging battery as infinity.
        $g_{bn} \leftarrow 0$                                    ▷ Starting time band not assigned.
        $r_{\text{assigned}} \leftarrow 0$                                        ▷ No charger assigned.
        for $r \in 1 \ldots R$ do
            for $m \in L_{bn}, \ldots, M$ do
                mincost $\leftarrow$ MinimumCost$(b, n, m, r, z, S)$
                if mincost $<$ cost$_{bn}$ then                       ▷ Starting here is cheaper.
                    $g_{bn} \leftarrow m$
                    $r_{\text{assigned}} \leftarrow r$
                end if
            end for
        end for
        for $m \in g_{bn}, \ldots, g_{bn} + I_b - 1$ do
            $z_{r_{\text{assigned}} m} \leftarrow 1$              ▷ Charger assigned is now in use for $I_b$ periods.
            $S_m \leftarrow S_m + \min\{F_{b,(m-g_{bn}+1)}, GS_m - S_m\}$   ▷ Update values for solar energy use.
        end for
        TotalCost $\leftarrow$ TotalCost $+$ cost$_{bn}$
    end for
end for
```

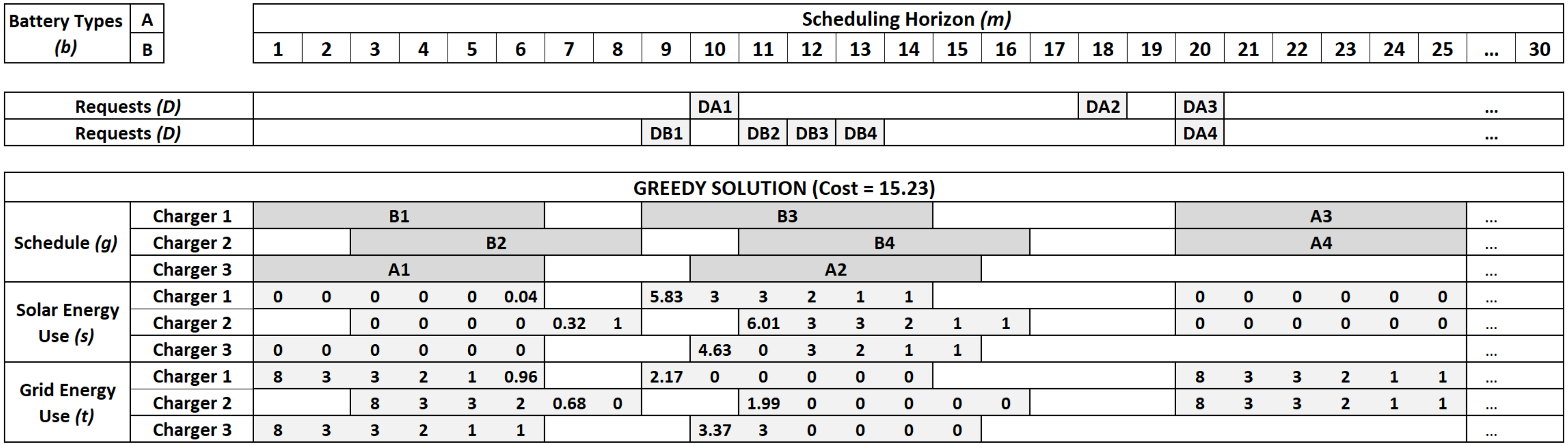
5.3. The effectiveness of the greedy algorithm

This subsection analyzes the effectiveness of the proposed greedy heuristic. We use some test instances for which CPLEX did not find any feasible solutions within a day. The computing time (CT) to obtain the first feasible solution (FS), the optimal solution (OS), the heuristic solution (HS), and their corresponding objective function values (OV) when the number of requests is 100, 200, 300 and 400, are in Table 2. Note that this constructive heuristic finds HS for industrial size instances in fewer than 10 seconds.

Requests	**FS OV**	**FS CT (s)**	**OS OV**	**OS CT (s)**	**HS OV**	**HS CT (s)**
100	-	>86400	-	>86400	549.29	<1
200	-	>86400	-	>86400	1,500.74	2.41
300	-	>86400	-	>86400	3,248.39	4.05
400	-	>86400	-	>86400	5,216.21	6.23

Table 2: Computational results.

Since the greedy heuristic finds just a feasible, not an optimal solution, it is appropriate to ask about the quality of this feasible solution. A first attempt to answer this question is to analyze the greedy schedule for the same illustrative example of Section 4.6. The latter is shown in Figure 4. With an optimality GAP of 12.5%, at first glance, the heuristic provides good solutions. In the next subsection, we address this question further with additional instances.



Battery Types *(b)*	
	A
	B

		Scheduling Horizon *(m)*																									
		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	...	30
Requests *(D)*											DA1								DA2		DA3						...	
Requests *(D)*										DB1		DB2	DB3	DB4							DA4						...	
GREEDY SOLUTION (Cost = 15.23)																												
Schedule *(g)*	Charger 1	B1								B3											A3						...	
	Charger 2			B2								B4									A4						...	
	Charger 3	A1									A2																...	
Solar Energy Use *(s)*	Charger 1	0	0	0	0	0	0.04			5.83	3	3	2	1	1						0	0	0	0	0	0	...	
	Charger 2			0	0	0	0	0.32	1			6.01	3	3	2	1	1				0	0	0	0	0	0	...	
	Charger 3	0	0	0	0	0	0				4.63	0	3	2	1	1											...	
Grid Energy Use *(t)*	Charger 1	8	3	3	2	1	0.96			2.17	0	0	0	0	0						8	3	3	2	1	1	...	
	Charger 2			8	3	3	2	0.68	0			1.99	0	0	0	0	0				8	3	3	2	1	1	...	
	Charger 3	8	3	3	2	1	1				3.37	3	0	0	0	0											...	

Figure 4: Greedy solution for the illustrative example.

5.4. The performance of greedy solutions

This subsection compares the performance of the MIP with the heuristic approach using the same test instances of Subsection 5.1. Table 3 reports the computing time (CT) to obtain the first feasible solution (FS), the heuristic solution (HS), their corresponding objective function values (OV) and GAPs. Note that the greedy approach provides quite competitive solutions. The heuristic and the MIP approaches obtain the same solutions up to 6 requests and five batteries. Moreover, except for small size instances (fewer than 12 requests), the greedy heuristic is Pareto-efficient compared to the first solution found by CPLEX providing faster and better solutions.

Battery Types	**Requests**	**FS OV**	**GAP**	**FS CT (s)**	**OS OV**	**OS CT (s)**	**HS OF**	**GAP**	**HS CT (s)**
1	6	8.56	0.00%	<1	8.56	<1	8.56	0.00%	<1
1	8	25.38	6.59%	<1	23.71	1.59	26.35	10.03%	<1
1	10	29.21	9.35%	1.31	26.48	2.17	29.63	10.64%	<1
1	12	39.84	14.32%	1.77	34.13	8.27	38.78	11.99%	<1
1	15	73.26	20.06%	2.15	58.56	166.6	65.91	11.15%	<1
1	20	95.74	21.73%	3.44	74.94	18,365.34	91.50	18.10%	<1
1	25	121.16	-	7.70	-	>86,400	97.68	-	<1
1	30	117.18	-	14.45	-	>86,400	109.54	-	<1
1	40	190.85	-	40.56	-	>86,400	138.11	-	<1
1	50	468.52	-	104.25	-	>86,400	235.12	-	<1
1	75	662.20	-	2077.99	-	>86,400	360.53	-	<1
5	6	10.29	0.00%	<1	10.29	<1	10.29	0.00%	<1
5	8	15.97	11.28%	<1	14.16	1.20	17.84	20.61%	<1
5	10	53.23	27.81%	1.21	38.43	10.71	49.77	22.79%	<1
5	12	68.57	27.69%	1.65	49.58	63.23	61.40	19.25%	<1
5	15	85.32	24.82%	2.21	64.14	26,336	71.78	10.64%	<1
5	20	98.06	-	9.94	-	>86,400	80.11	-	<1
5	25	135.03	-	25.38	-	>86,400	100.70	-	<1
5	30	178.50	-	67.56	-	>86,400	129.29	-	<1
5	40	276.31	-	4417.95	-	>86,400	182.90	-	<1
5	50	-	-	>86,400	-	>86,400	276.79	-	<1
5	75	-	-	>86,400	-	>86,400	482.10	-	<1
10	6	12.42	0.00%	<1	12.42	<1	12.76	2.68%	<1
10	8	32.55	17.42%	<1	26.88	1.78	33.24	19.14%	<1
10	10	62.21	29.85%	1.06	43.64	7.00	55.72	21.67%	<1
10	12	68.71	20.99%	1.12	54.28	24.09	65.61	17.27%	<1
10	15	120.50	-	1.48	-	>86,400	87.51	-	<1
10	20	111.11	-	4.32	-	>86,400	79.91	-	<1
10	25	168.87	-	7.97	-	>86,400	108.47	-	<1
10	30	223.89	-	12.63	-	>86,400	134.05	-	<1
10	40	261.98	-	484.36	-	>86,400	240.84	-	<1
10	50	-	-	>86,400	-	>86,400	314.38	-	<1
10	75	-	-	>86,400	-	>86,400	523.51	-	<1

Table 3: Performance of greedy solutions.

We have also conducted a statistical analysis to compute an average GAP of the greedy solution and the first CPLEX solutions relative to the optimal solution. We have computed these three solutions for 90 instances stratified by the number of requests: 30 instances with 10, 12 and 14 requests. Figure 5 reports the results. The average greedy and first CPLEX solution GAP are 9.67% and 17.33% respectively. The standard deviation is always smaller for the greedy heuristic than the first CPLEX solution, indicating that the greedy heuristic

provides more robust solutions than the first CPLEX solutions.

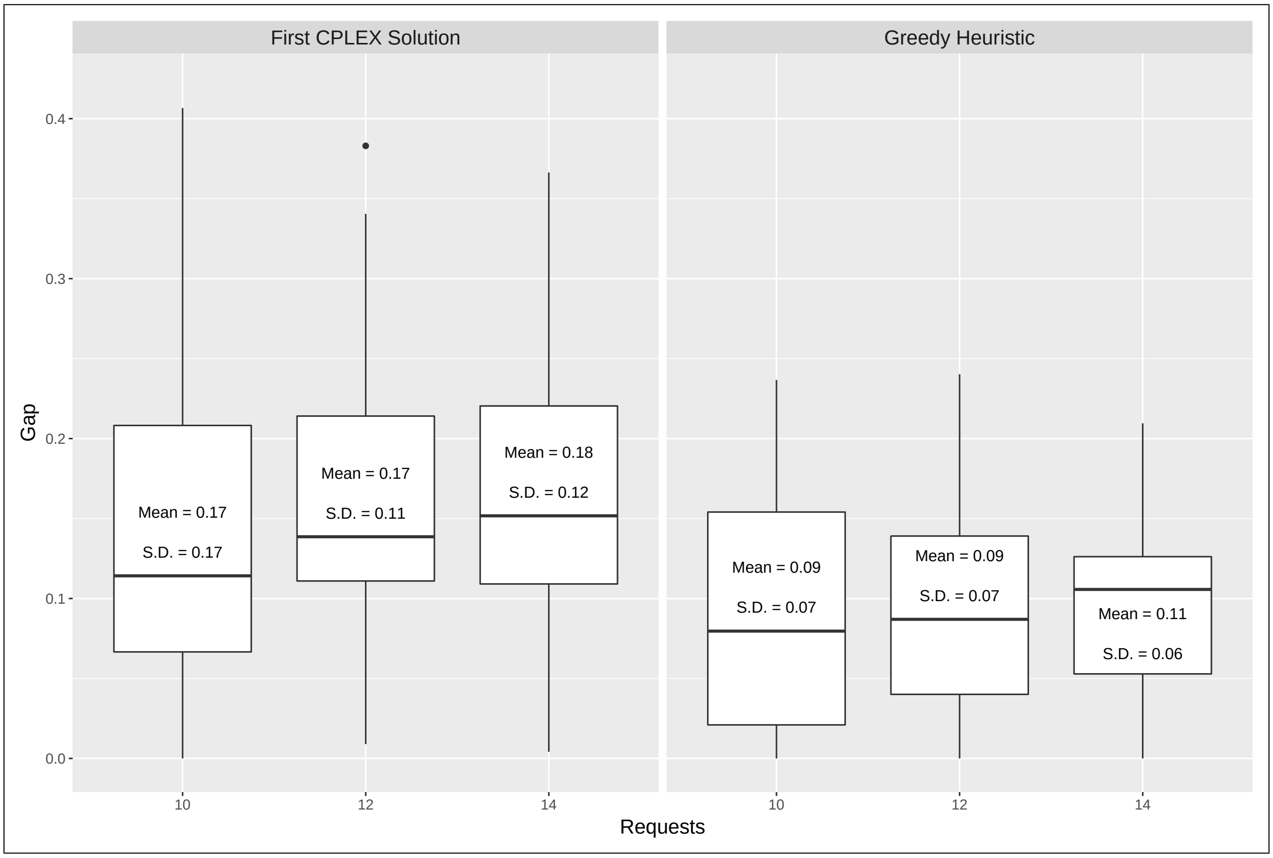


Figure 5: GAP performance.

6. Concluding Remarks

Operations that consume energy such as stacking pallets in warehouses are increasingly replacing fossil fuels with electric power. This replacement evolves more rapidly where renewable energy is available and carries with it environmental and economic advantages.

This paper addresses the allocation of discharged batteries to chargers in a battery center of a warehouse, where a Chilean company we worked with, operates stackers of its business. Grid electric energy varies by hour of the day, and solar energy is available almost freely. The objective of this research is to determine a charging schedule which minimizes a combination of energy consumption and delays costs.

The battery charge-scheduling problem this paper models is relevant to the operations of logistics centers worldwide in environments with competitive markets and not steady energy tariffs. Moreover, manufacturing systems are increasingly using EVs to move cargo in logistics centers and warehouses, which increases the effects of battery charging management.

This paper presents two approaches to address this problem. First, we propose a MIP model, but the computation times render this approach impractical, which precludes its use in industrial instances. Second, we offer a trial and error heuristic approach that finds a feasible solution in reasonable computing times even for real cases. For small instances, with ≤ 25 requests, we obtain an optimal solution with the

MIP approach. For medium size instances, between 25 and 75 requests, CPLEX finds only sub-optimal solutions. These solutions have worse objective function value and spend more computing time than our heuristic solution. For instances for $\geq$ 100 requests, CPLEX is unable to find any solution whereas our heuristic approach finds solutions in a matter of seconds with a computed mean GAP of 9.67%.

This approach uses requests time band-specific counts for charged batteries arriving to the BC. Further research could analyze the model behavior when one incorporates uncertainty into the prediction of counts of batteries. Another line of research could be how to integrate the charging scheduling problem into electric cargo vehicle management systems. Due the course of dimensionality, we expect that a robust optimization approach under a rolling horizon scheme could be more suitable in this environment than a multi-stage stochastic programming approach. Finally, while we have focused on developing a greedy construction heuristic to obtain feasible solutions from scratch in reasonable computing times, we left to future research the improvement of the quality of the incumbent solution by using metaheuristics such as tabu search, simulated annealing, genetic algorithms, and so on.

Appendix A: Illustrative Example Data

Tables A1–A6 in this appendix show the data and parameters our illustrative example uses.

Parameters	Value	Indexes and their ranges
B	2	$b \in \{1, \ldots, B\}$
R	3	$r \in \{1, \ldots, R\}$
M	30	$m \in \{1, \ldots, M\}$
N_b	6 $\forall b$	$n \in \{1, \ldots, N_b\}$
K_b	4 $\forall b$	$k \in \{1, \ldots, K_b\}$
I_b	6 $\forall b$	$i \in \{1, \ldots, I_b\}$

Table A1. Indexes, parameters and their ranges.

Parameters	Values
RS_b	2 $\forall b$
S_b	0 $\forall b$
SOL_r	1 $\forall r$
CS_m	0.03 $\forall m$
$DISCH_{bn}$	1 $\forall b, n$
CH_{bn}	1 $\forall b, r$
W_1	0.350
W_2	0.400

Table A2. Parameters and their values.

m	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
CG_m	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
GS_m	0	0	0	0	0	0.04	0.32	2.65	5.83	7.63	9.01	9.83	10.98	10.45	8.28

m	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
CG_m	0.08	5	5	5	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
GS_m	6.78	4.03	1.89	0.11	0	0	0	0	0	0	0	0	0	0	0

Table A3. Cost of grid energy (CG_m) and solar energy availability (GS_m) during time bands $m \in \{1, \ldots, M\}$.

			Charging TB					
		F_{bi}	1	2	3	4	5	6
Battery	Type	1	8	3	3	2	1	1
		2	8	3	3	2	1	1

Table A4. Energy requirement of battery $b \in \{1, \ldots, B\}$ in TB $i \in \{1, \ldots, I_b\}$ of charge.

			Battery Number					
		L_{bn}	1	2	3	4	5	6
Battery	Type	1	0	0	10	18	20	20
		2	0	0	9	11	12	13

Table A5. Lower bound for initial charging TB of battery $n \in \{1, \ldots, N_b\}$ of type $b \in \{1, \ldots, B\}$.

			Request Number			
		D_{bk}	1	2	3	4
Battery	Type	1	10	18	20	20
		2	9	11	12	13

Table A6. TB of request $k \in \{1, \ldots, K_b\}$ of type $b \in \{1, \ldots, B\}$.

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