A Position Allocation Approach to the Scheduling of Battery Electric Bus Charging

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ABSTRACT

Dependable charging schedules for an increasing interest of battery electric bus (BEB) fleets is a critical component to a successful adoption. In this paper, a BEB charging scheduling framework that considers spatiotemporal schedule constraints, route schedules, fast and slow charging, and battery charging dynamics is modeled as a mixed integer linear program (MILP). The MILP is modeled after the berth allocation problem (BAP) in a modified form known as the position allocation problem (PAP). Linear battery dynamics are included to model the charging and discharging of buses while at the station and during their routes, respectively. The optimization coordinates BEB charging to ensure each BEB has sufficient charge while using slow chargers where possible for sake of battery health. The model also minimizes the total number of chargers utilized and prioritizes slow chargers. The model validity is demonstrated with a set of routes sampled from Utah Transit Authority (UTA) for 35 buses and 338 visits to the charging station. The model is also compared to a heuristic based algorithm, referred to as the Quin-Modified method. The results presented show that the slow chargers are more readily selected and the charging and spatiotemporal constraints are met while considering the battery dynamics, minimizing the charger count, and consumption cost. The results are also compared to that of the Quin-Modified schedule.

Keywords: Berth Allocation Problem (BAP), Position Allocation Problem (PAP), Mixed Integer Linear Program (MILP), Battery Electric Bus (BEB), Scheduling at least 5 are mandatory.

1 INTRODUCTION

The public transportation system is crucial in any urban area; however, the increased awareness and concern of environmental impacts of petroleum based public transportation has driven an effort to reduce the pollutant footprint [4, 26, 7, 12]. Particularly, the electrification of public bus transportation via battery power, i.e., battery electric buses (BEBs), has received significant attention [12]. Although the technology provides benefits beyond reduction in emissions, such as lower driving costs, lower maintenance costs, and reduced vehicle noise, battery powered systems introduce new challenges such as larger upfront costs, and potentially several hours long "refueling" periods [26, 12]. Furthermore, the problem is exacerbated by the constraints of the transit schedule to which the fleet must adhere, the limited amount of chargers available, and the adverse affects in the health of the battery due to fast charging [14]. This paper presents a continuous scheduling framework for a BEB fleet that shares limited fast and slow chargers. This framework takes into consideration linear charging dynamics and a fixed bus schedule while meeting a certain battery charge threshold throughout the day.

Many recent efforts have been made simultaneously solve the problems of scheduling and charging fleets and determining the infrastructure upon which they rely, e.g., [25, 20, 10, 24]. The added complexity of considering both the BEB charge scheduling and the infrastructure problems necessitates simplifications for sake of computation of the charge scheduling problem. Further complexities are introduced in the form of schemes to introduce BEBs into existing fleets by replacing existing buses [28, 18, 5], assigning BEBs to routes, and introducing uncertainties into the models [21, 5]. These simplifications to the charge scheduling model include utilizing only fast chargers while planning [25, 20, 24, 29, 13, 27, 23, 17]. If slow chargers

are used, they are only employed at the depot and not the station [9, 21]. Some approaches assume full charge [25, 24, 29, 23]. Others have assumed that the charge received is proportional to the time spent on the charger [13, 27], which can be a valid assumption when the battery state-of-charge (SOC) is below 80% charge [13].

This work builds upon the Position Allocation Problem, a modification of the well studied Berth Allocation Problem (BAP), as a means to schedule the charging of electric vehicles [16, 1, 6, 11]. The BAP is a continuous time model that solves the problem of allocating space for incoming vessels to be berthed. Each arriving vessel requires both time and space to be serviced and is assigned a berthing location [11]. Vessels are lined up parallel to the berth to be serviced and are horizontally queued as shown in Fig 1. The PAP utilizes this notion of queuing for scheduling vehicles to be charged, as shown in Fig 2. The PAP is formulated as a rectangle packing problem by assuming that vehicle charging will take a fixed amount of time, the amount of vehicles that can charge is limited by the physical width of the vehicles, and each vehicle visits the charger a single time [16].

The main contribution of this work is the extension of the PAP novel approach to BEB charger scheduling. This includes modeling and incorporation of a proportional charging model into the MILP framework, consideration of multiple charger types, and inclusion of the route schedule for each bus. The result is a MILP formulation that coordinates charging times and charger type for every visit that each bus makes to the station while considering a dynamic charge model and scheduling constraints.

The remainder of the paper proceeds as follows: In Section 2, the PAP is introduced with a formulation of the resulting MILP. Section 3 constructs the MILP for BEB scheduling, including modifications to the PAP queuing constraints and development of a dynamic charging model. Section 4 demonstrates an example of using the formulation to coordinate 35 buses over 338 total visits to the station. The paper ends in Section 5 with concluding remarks.

2 THE POSITION ALLOCATION PROBLEM

The BEB charge schedule formulation in this work builds upon the PA, which, in turn, builds upon the BAP. This section provides a brief overview of the BAP and a detailed formulation of PAP as presented in [16].

2.1 Overview of BAP

The BAP is a rectangle packing problem where a set of rectangles ($\mathbb{O}$) are attempted to be optimally placed in a larger rectangle (O) as shown in Fig 3. The rectangle packing problem is an NP-hard problem that can be used to describe many real life problems [3, 15]. In some of these problems, the dimensions of $\mathbb{O}$ are held constant such as in the problem of packing modules on a chip, where the widths and height of the rectangles represent the physical width and heights of the modules [15]. Other problems, such as the BAP, in some formulations, allow one side of the rectangle to vary depending on its assigned position (i.e. the handling time is dependent on the berth) [1].

The BAP solves the problem of optimally assigning incoming vessels to berth positions to be serviced (Fig 1). The width and height of O represent the berth length S and time horizon T, respectively. Similarly, the width and height for $\mathbb{O}$ represent the time spent to service vessel i and the space taken by docking vessel i, respectively. The vessel characteristics (length of the vessel, arrival time, handling time, desired departure time) are assumed to be known for all N vessels to be serviced. A representation of a BAP solution is shown in Fig 4.

The BAP objective is generally represented as minimizing some operational time for a given vessel i. The operational time may be chosen to minimize the difference between arrival and departure times, time spent being serviced, or overall waiting time [22, 1, 6]. The model must then constrain the vessel placement as to not allow overlap spatially or temporally.

2.2 The PAP Formulation

The BAP formulation forms the basis of the PAP; however, there are some differences in the way the variables are perceived. For the ith visit, starting service time, u_i, is now the starting charge time, the berth location, v_i, is now the charger queue for assignment, and the service time, p_i, is now the time to charge. The PAP utilizes a number of parameters. The following parameters are constants.

88   • S : charger length
89   • T : time horizon
90   • N : number of incoming vehicles
91   • p_i : charging time for vehicle i; $1 \leq i \leq N$
92   • s_i : width of vehicle i; $1 \leq i \leq N$
93   • a_i : arrival time of vehicle i; $1 \leq i \leq N$

94   These constants define the problem bounds. The following list provides a series of decision variables
95   used in the formulation.

96   • u_i : starting time of service for vehicle i; $1 \leq i \leq N$
97   • v_i : charge location i; $1 \leq i \leq N$
98   • c_i : departure time for vehicle i; $1 \leq i \leq N$
99   • σ_{ij} : binary variable that determines ordering of vehicles i and j in time
100   • δ_{ij} : binary variable that determines relative position of vehicles i and j when charging simultaneously

101   To determine the values for each of these decision variables, a MILP is formulated in [16] and shown
102   here for sake of completeness.

$$\min \sum_{i=1}^{N}(c_i - a_i) \tag{1}$$

Subject to:

$$u_j - u_i - p_i - (\sigma_{ij} - 1)T \geq 0 \tag{2a}$$
$$v_j - v_i - s_i - (\delta_{ij} - 1)S \geq 0 \tag{2b}$$
$$\sigma_{ij} + \sigma_{ji} + \delta_{ij} + \delta_{ji} \geq 1 \tag{2c}$$
$$\sigma_{ij} + \sigma_{ji} \leq 1 \tag{2d}$$
$$\delta_{ij} + \delta_{ji} \leq 1 \tag{2e}$$
$$p_i + u_i = c_i \tag{2f}$$
$$a_i \leq u_i \leq (T - p_i) \tag{2g}$$
$$\sigma_{ij} \in \{0,1\},\ \delta_{ij} \in \{0,1\} \tag{2h}$$
$$v_i \in [0\ S] \tag{2i}$$

103   The objective function (1) minimizes the time spent to service each vehicle by minimizing over the sum
104   of differences between the departure time, c_i, and arrival time, a_i. i.e., It seeks to get each vehicle charged
105   and on its way as quickly as possible.

106   Constraints 2a-2e are used to ensure that individual rectangles do not overlap. For the PAP, they ensure
107   that two vehicles charging simultaneously are at different positions and, similarly, two vehicles that have
108   overlapping positions do not overlap temporally. Constraint (2a) establishes temporal ordering when active
109   ($\sigma_{ij} = 1$). Similarly, when $\delta_{ij} = 1$ in (2b) then spatial ordering is established. Constraints 2c-2e enforce
110   that spatial and/or temporal ordering is established between each possible vehicle pair. Constraints (2d)
111   and (2e) enforce consistency. For example, (2d) enforces that vehicle i cannot come before vehicle j and
112   vehicle j simultaneously come before vehicle i.

113   The last constraints force relationships between arrival time, charge start time, and departure time.
114   Constraint (2f) states that the service start time, u_i, plus the time to service vehicle i, p_i, must equal the
115   departure time, c_i. Constraint (2g) enforces the arrival time, a_i, to be less than or equal to the service start
116   time, u_i, which in turn must be less than or equal to the latest time the vehicle may begin to be serviced to
117   stay within the time horizon. Constraint (2h) ensures that σ_{ij} and δ_{ij} are binary. Constraint (2i) ensures
118   that the assigned value of v_i is a valid charging position.

3 PROBLEM FORMULATION

119 Applying the PAP to BEB charging requires four fundamental changes. The first is that the time that a
120 BEB spends charging is allowed to vary. Thus, p_i becomes a variable of optimization. Second, in the PAP
121 each charging visit is assumed to be a different vehicle. For the BEB charging problem, each bus may
122 make multiple visits to the station throughout the day and the resulting charge for a bus at a given time is
123 dependent upon each of the prior visits made. Third, in the PAP, the charger is one continuous bar with
124 vehicle width effectively restricting the number of vehicles charging simultaneously. For the BEB, it is
125 assumed that a specific number of chargers exist, and these chargers can charge the vehicle at a different
126 rate. The fourth fundamental change is related to the first three. The charge of each bus must be tracked in
127 the optimization to ensure that charging across multiple visits is sufficient to allow each bus to execute its
128 route throughout the day.

129 The discussion of the four changes are separated into two sections. Section 3.1 discusses the changes in
130 the spatial-temporal constraint formulation to form a queuing constraint. Section 3.2 then discusses the
131 addition of the bus charge management. This section ends with a brief discussion of a modified objective in
132 Section **??** and the statement of the full problem in Section 3.3. The notation is explained throughout and
133 summarized in Table 1.

3.1 Queuing Constraints

135 The queuing constraints help to ensure that the busses enter queues for charging or waiting as they come
136 into the station. There are three sets to differentiate between different entities. $\mathbb{B} = \{1, ..., n_B\}$ is the set of
137 bus indices with index b used to denote an individual bus, $\mathbb{Q} = \{1, ..., n_Q\}$ is the set of queues with index q
138 used to denote an individual queue, and $\mathbb{V} = \{1, ..., n_V\}$ is a set of visits to the station with i, j used to
139 refer to individual visits. The mapping $\Gamma : \mathbb{V} \to \mathbb{B}$ is used to map a visit index to a bus index with the
140 shorthand Γ_i used to refer to the bus index for visit i.

141 Most variables are now defined in terms of a visit. Two separate visits could correspond to different buses
142 or visits by the same bus. The spatial variable s_i is removed and v_i is made to be an integer corresponding
143 to which queue visit i will be using. Thus, when $\delta_{ij} = 1$, the visits must be at different chargers, i.e.,
144 $v_i - v_j \geq 1$. The variable S is likewise replaced with n_Q. Note that $n_Q = n_B + n_C$, where n_B is the
145 number of busses and n_C is the number of chargers. The rationale for having extra queues is to allow buses
146 to sit idle instead of charging. The modified queuing constraints can be written as follows.

$$u_i - u_j - p_j - (\sigma_{ij} - 1)T \geq 0 \tag{3a}$$
$$v_i - v_j - (\delta_{ij} - 1)n_Q \geq 1 \tag{3b}$$
$$\sigma_{ij} + \sigma_{ji} + \delta_{ij} + \delta_{ji} \geq 1 \tag{3c}$$
$$\sigma_{ij} + \sigma_{ji} \leq 1 \tag{3d}$$
$$\delta_{ij} + \delta_{ji} \leq 1 \tag{3e}$$
$$p_i + u_i = c_i \tag{3f}$$
$$a_i \leq u_i \leq (T - p_i) \tag{3g}$$
$$c_i \leq \tau_i \tag{3h}$$
$$p_i \geq 0 \tag{3i}$$
$$\sigma_{ij} \in \{0, 1\}, \ \delta_{ij} \in \{0, 1\} \tag{3j}$$
$$v_i \in \mathbb{Q} \tag{3k}$$

147 Constraints (3a)-(3g) and (3j) are nearly identical to those described in Section 2 with the sole change
148 in (3b) being described above to conform to a queue. Constraint (3h) is added to ensure that the ending
149 charge time, c_i, must be less than or equal to the required departure time from the station, τ_i. This enables
150 the bus schedules to be considered during optimization. Finally, (3k) enforces v_i to be an integer in the set
151 of possible queues.

3.2 Battery Charge Dynamic Constraints

Using purely the constraints in (3) with the objective in (1) would result in c_i being chosen as small as possible by employing $p_i = 0$, $u_i = c_i$. Thus, the vehicles would not charge. Furthermore, it does not encode any revisiting of the BEB to the charging station. To remedy this, battery dynamic constraints are introduced.

Battery charge dynamic constraints are used to model the charge in each bus with the purpose of ensuring sufficient time is spent charging. Two constraints are enforced on the bus charge: busses must always have sufficient charge to execute their respective routes and each bus must end the day with a specific charge threshold, preparatory to execution for the next day.

The charge at the beginning of visit i is denoted as η_i. As a charge on the bus is dependent upon the visits that bus makes to the station, the mapping $\Upsilon : \mathbb{V} \to \mathbb{V} \bigcup \{\varnothing\}$ is used to determine the next visit that corresponds to the same bus, with Υ_i being shorthand notation. Thus, Γ_i and Γ_{Υ_i} would both map to the same bus index as long as Υ_i is not the null element, $\varnothing$. The null element is used to denote that there are no future visits by that same bus.

To drive time spent on the charger, p_i, as well as define initial, final, and intermediate bus charges for each visit i, the sets for initial and final visits must be defined. Let the mapping of the first visit by each bus be denoted as $\Gamma_i^0 : \mathbb{V} \to \mathbb{V} \bigcup \{\varnothing\}$. The indexed value of Γ_i^0 represents the index for the first visit of bus b or the null element, $\varnothing$. Similarly, let $\Gamma_i^f : \mathbb{V} \to \mathbb{V} \bigcup \{\varnothing\}$ contain the indexes for the final visit of each bus b or the null element. The initial and final bus charges can then be represented by the constraint equations $\eta_{\Gamma_i^0} = \alpha \kappa_{\Gamma_i^0}$ and $\eta_{\Gamma_i^f} = \beta \kappa_{\Gamma_i^f}$, respectively, where α and β are percentages of the battery for first and final visit, respectively. The intermediate charges must be determined at solve time.

It is assumed that the charge received is proportional to the time spent charging. The charge rate for charger q is denoted as r_q. Note that a value of $r_q = 0$ corresponds to a queue where no charging occurs. A bus in such a queue is simply waiting for the departure time. Thus, $n_Q = n_C + n_B$ where the final n_B queues have $r_q = 0$ to allow an arbitrary number of buses to not charge at any given moment in time. The amount of discharge between visits i and Υ_i, the next visit of the same bus, is denoted as λ_i. If visit i occurred at charger q, the charge of the bus coming into visit Υ_i would be

$$\eta_{\Upsilon_i} = \eta_i + p_i r_q - \lambda_i. \tag{4}$$

The binary decision variable w_{iq} is introduced to determine whether visit i uses charger q. This allows the charge of the bus coming into visit Υ_i to be written in summation form as

$$\eta_{\Upsilon_i} = \eta_i + \sum_{q=1}^{n_Q} p_i w_{iq} r_q - \lambda_i \tag{5a}$$

$$\sum_{q=1}^{n_Q} w_{iq} = 1 \tag{5b}$$

$$w_{iq} \in \{0, 1\} \tag{5c}$$

The choice of queue for visit i, v_i, becomes a slack variable and is defined in terms of w_{iq} as

$$v_i = \sum_{q=1}^{n_Q} q w_{iq} \tag{6}$$

Maximum and minimum values for the charges are included to ensure the battery is not overcharged and to guarantee sufficient charge for subsequent visits. The upper and lower battery charge bounds for bus b

184 are κ_b and ν_b, respectively. As η_i corresponds to the charge at the beginning of the visit, the upper bound
185 constraint must also include the charge received during the visit as follows.

$$\eta_i + \sum_{q=1}^{n_Q} p_i w_{iq} r_q \leq \kappa_{\Gamma_i} \tag{7a}$$

$$\eta_i \geq \nu_{\Gamma_i} \kappa_{\Gamma_i} \tag{7b}$$

186 Note that the term $p_i w_{iq}$ is a bilinear term (two decision variables being multiplied together) which
187 is nonlinear [19]. A standard way of linearizing a bilinear term that contains an integer variable is by
188 introducing a slack variable with an either/or constraint [2, 19]. Allowing the slack variable g_{iq} to be equal
189 to $p_i w_{iq}$, g_{iq} can be defined as

$$g_{iq} = \begin{cases} p_i & w_{iq} = 1 \\ 0 & w_{iq} = 0 \end{cases}. \tag{8}$$

190 Equation (8) can be expressed as a mixed integer constraint using big-M notation with the following four
191 constraints.

$$p_i - (1 - w_{iq})M \leq g_{iq} \tag{9a}$$

$$p_i \geq g_{iq} \tag{9b}$$

$$M w_{iq} \geq g_{iq} \tag{9c}$$

$$0 \leq g_{iq} \tag{9d}$$

192 where M is a large value. If $w_{iq} = 1$ then (9a) and (9b) become $p_i \leq g_{iq}$ and $p_i \geq g_{iq}$, effectively stating
193 $p_i = g_{iq}$ with (9c) being inactive. If $w_{iq} = 0$, (9a) is inactive and (9c) and (9d) force $g_{iq} = 0$.

3.3 The BEB Charging Problem

195 The goal of the MILP is to utilize chargers as little as possible to reduce energy costs with the fast
196 charging penalized greater to reduce battery damage. Thus, an assignment cost m_q and usage cost ϵ_q are
197 associated with each charger, q. The cost for both the assignment and utilization of slow chargers is less
198 than that of the fast chargers. The objective function has an assignment term, $w_{iq} m_q$, which is non-zero if
199 charger q is used for visit i. Similarly, a usage term $g_{iq} \epsilon_q$ is non-zero only if charge is received for visit i at
200 charger q. The resulting objective is defined in Eq 10. The assignment cost, $w_{iq} m_q$, and the usage cost,
201 $g_{iq} \epsilon_q$, are summed over each visit, i, and charger, q.

$$\min \sum_{i=1}^{N} \sum_{q=1}^{n_Q} \left(w_{iq} m_q + g_{iq} \epsilon_q \right) \tag{10}$$

202 Subject to the constraints in Eq 11.

$$u_i - u_j - p_j - (\sigma_{ij} - 1)T \geq 0 \tag{11a}$$

$$v_i - v_j - (\delta_{ij} - 1)n_Q \geq 1 \tag{11b}$$

$$\sigma_{ij} + \sigma_{ji} + \delta_{ij} + \delta_{ji} \geq 1 \tag{11c}$$

$$\sigma_{ij} + \sigma_{ji} \leq 1 \tag{11d}$$

$$\delta_{ij} + \delta_{ji} \leq 1 \tag{11e}$$

$$p_i + u_i = c_i \tag{11f}$$

$$a_i \leq u_i \leq (T - p_i) \tag{11g}$$

$$c_i \leq \tau_i \tag{11h}$$

$$\eta_{\Gamma_i^0} = \alpha \kappa_{\Gamma_i^0} \tag{11i}$$

211
$$\eta_i + \sum_{q=1}^{n_Q} g_{iq} r_q - \lambda_i = \eta_{\gamma_i} \quad \text{(11j)}$$

212
$$\eta_i + \sum_{q=1}^{n_Q} g_{iq} r_q - \lambda_i \geq \nu \kappa_{\Gamma_i} \quad \text{(11k)}$$

213
$$\eta_i + \sum_{q=1}^{n_Q} g_{iq} r_q \leq \kappa_{\Gamma_i} \quad \text{(11l)}$$

214
$$\eta_{\Gamma_i^f} \geq \beta \kappa_{\Gamma_i^f} \quad \text{(11m)}$$

215
$$p_i - (1 - w_{iq})M \leq g_{iq} \quad \text{(11n)}$$

216
$$p_i \geq g_{iq} \quad \text{(11o)}$$

217
$$M w_{iq} \geq g_{iq} \quad \text{(11p)}$$

218
219
$$0 \leq g_{iq} \quad \text{(11q)}$$

$$v_i = \sum_{q=1}^{n_Q} q w_{iq} \quad \text{(11r)}$$

220
$$\sum_{q=1}^{n_Q} w_{iq} = 1 \quad \text{(11s)}$$

221
$$w_{iq} \in \{0, 1\} \quad \text{(11t)}$$

222
$$\sigma_{ij} \in \{0, 1\}, \ \delta_{ij} \in \{0, 1\} \quad \text{(11u)}$$

223
$$v_i \in \mathbb{Q} \quad \text{(11v)}$$

224
$$i \in \mathbb{V} \quad \text{(11w)}$$

225
$$q \in \mathbb{Q} \quad \text{(11x)}$$

226 Constraints (11a)-(11h) are reiterations of the queuing constraints in (3). Constraints (11i)-(11m) provide
227 initialization and terminal conditions as well as intermediate constraints to provide continuity in vehicle
228 charges. Constraint (11i) states the first arrival for each bus is initialized with a charge of $\alpha \kappa_{\Gamma_i^0}$. Constraints
229 (11j), (11k), and (11l) define the battery charge dynamics using (5) and (7) with the gain slack variables
230 g_{iq} used in place of the bilinear term. Constraints (11n) through (11q) define g_{iq} using (9).

231 Constraint (11l) ensures that the charging done for visit i cannot be greater than the capacity of the
232 battery, κ_{Γ_i}. Constraint (11m) states that the last visit for each vehicle must have a minimum charge of
233 $\beta \kappa_{\Gamma_i^f}$, guaranteeing a minimum initial charge for the next working day. The last constraints (11t)-(11x)
234 define the sets of valid values for each variable.

4 EXAMPLE

235 An example will now be presented to demonstrate the utility of the developed MILP charge scheduling
236 techique. A description of the scenario is first presented followed a description of an alternative heuristic
237 based planning strategy called Quin-Modified which is used as a comparison to the MILP PAP. Results are
238 then presented for each of planning strategies are presented, analyzed, and discussed.

4.1 BEB Scenario

240 To display the capabilities of the model, an example scenario is presented. The scenario was ran over a
241 time horizon of $T = 24$ hours, utilizes $A = 35$ buses with $N = 338$ visits to the station divided between
242 the A buses. Each bus has a 388 KWh battery that is required to stay above 25% charge (3589 KWh) to
243 maintain battery health, and the bus is assumed to begin the working day with 90% charge (349.2 KWh).
244 Additionally, each bus is required to end the day with a minimum charge of 70% (271.6 KWh). Each bus is
245 assumed to discharge at a rate of 30 KWh. Note that there are many factors that play a factor in the rate of
246 discharge; however, for the sake of simplicity an average rate is used. $n_C = 30$ chargers are utilized where
247 15 of the chargers are slow charging (30 KWh) and 15 are fast charging (911 KWh).

248 To encourage the MILP PAP problem to utilize the fewest number of chargers, the value of m_q in the
249 objective function, (10), is $\forall q \in Q; m_q = 1000q$. The charge duration scalar, ϵ_q, is defined as $\epsilon_q = r_q$
250 to create a consumption cost term, $g_{iq} \epsilon_q$. This is utilized to also encourage the model to minimize active
251 charger times, especially for the fast chargers.

252 Another heuristic-based optimization strategy, referred to as Quin-Modified, is also employed as a means
253 of comparison with the results of the MILP PAP. The Quin-Modified strategies is a based on the threshold
254 strategy of [17]. The strategy has been modified slightly to accommodate the case of multiple charger types
255 and without exhaustive search for the best charger type. The heuristic is based on a set of rules that revolve

around the initial charge of the bus at visit i. There are three different thresholds, low (60%), medium (75%), and high (90%). Buses below the low threshold are prioritized to fast chargers then are allowed to utilize slow chargers if no fast chargers are available. Buses between the low and medium threshold prioritize slow chargers first and utilize fast chargers only if no slow chargers are available. Buses above the medium threshold and below high will only be assigned to slow chargers. Buses above the high threshold will not be charged. Once a bus has been assigned to a charger, it remains on the charger for the duration of the time it is at the station, or it reaches 90% charge, whichever comes first.

The schedule is sampled from the Utah Transit Authority (UTA) To do: is it? bus routing data that occurs over a 24-hour time period. The total number of constraints resulted in 11830 continuous and 238628 integer/binary constraints. The optimization was performed using the Gurobi MILP solver [8] on a machine running an AMD Ryzen 9 5900X 12 - Processor (24 core) at 4.95GHz. The solver was allowed to run for 14400 seconds and did not converge to the optimal result with a gap 52.5% .

4.2 Results

The schedule generated by the Quin-Modified strategy and the MILP PAP is shown in Fig 6a and Fig 6b, respectively. The x-axis represents the time in hours. The y-axis represents the assigned charger. Points between zero and 14 are active times for slow chargers, and points between the range of 14 and 29 are active times for fast chargers. The filled symbol represents the starting charge time for a bus b with the line to the vertical tick signifying the region of time the charger is active. The line connecting points represent the charge sequence for a bus. Each color in Fig 6a and 6b are used to identify the bus assigned.

The first observation is in the choice of preferred chargers between the Quin-Modified and MILP scheduler. The Quin-Modified schedule uses at most 4 fast chargers and 3 slow whereas the MILP schedule uses at most 2 fast chargers and 8 slow, the eighth charger actually being the ninth queue, but that is due to the non-optimal results. Both the Quin-Modifed and MILP schedule used the fast chargers in short bursts (0.2-0.5 hours). The main difference lies in the utilization strategy of the slow chargers. The Quin-Modified, for the most part, opted for shorter bursts for the slow chargers (0.3-0.7 hour), most heavily placed on the first slow charger. The MILP also used these shorter charge times on the first slow charger; however, the schedule was able to recognize the bus routes that had longer durations at the station and could choose the lower cost option, slow charging, when available and of lower cost. Although one the MILP's objectives is to minimize the amount of chargers used, the Quin-Modified ended up using 7 chargers while the MILP used 8. The reason for this is the construction of the objective function that is attempting to optimize over the consumption cost, total number of chargers, and charger type. Hence, the objective function found it more efficient to utilize an extra slow charger for a longer duration than to add another fast charger for a short duration. Although both schedules generated are valid, no comparison of the quality the schedule can be made.

Figs 7a and 7b depicts the charge for every bus over the time horizon. Every vehicle begins at 90% charge, finishes at 70% charge in the MILP PAP schedule, and never goes below 25% in the intermediate arrivals as stated in the constraints (11). There is no guarantee for this in the Quin-Modified strategy which can be seen by some of the bus charges reaching negative values and the distribution of final charges. The only sense of guarantee that the Quin-Modified supplies is its predictability within the intermediate visits because of the heuristic nature (i.e. if the charge the low threshold, a fast charger will be prioritized) whereas MILP places a bus in the queue that "makes sense" in respect to the larger picture. The MILP PAP does not have an obvious sense of decision-making due to its weighted decisions that are affected by the accumulation of decisions made prior.

Another important measure for the chargers is to compare the amount of power and energy consumed. Fig 8 depicts the power consumption throughout the time horizon. It can easily be seen that the Quin-Modifed power consumption is steadily less than the MILP schedule. This can be accounted for by the MILP's constraints to keep the bus charges above 25% and to reach the 70% charge at the end of the working day. It is also important to note that largest peak for the Quin-Modified schedule verses the lack of any real peak for the MILP PAP schedule. Although the MILP PAP had firmer constraints than the Quin-Modified algorithm, it maintained a steady power consumption profile throughout the time horizon. Along a similar vein, the accumulated energy consumed is shown in Fig 9. The MILP schedule is more efficient up until about hour 11. Again, this can be accounted for by the fact the MILP is accommodating the extra constraints. Even with these constraints, MILP PAP consumes about $1 \cdot 10^5$ Kwh more than the Quin-Modified. The overlap

309 of the MILP PAP can be accounted for by Fig 10a and 10b. At the 11th hour, a spike in slow chargers can
310 be seen in an attempt to keep the bus charges above the 25% charge and preparing to meet the final 70%
311 constraint.

5 CONCLUSION

312 This work developed a MILP scheduling framework that optimally assigns slow and fast chargers to a BEB
313 bus fleet assuming a constant schedule. The BAP was introduced with an example formulation and was
314 then compared to the PAP. The PAP constructed on the BAP to allow the time spent on the charger, p_i,
315 to be a decision variable. Because the original PAP required service time, p_i, to be given, linear battery
316 dynamics were introduced to drive charging times. Additional constraints were also introduced to provide
317 limits for the battery dynamics.

318 An example for the MILP PAP formulation was then presented and compared to a heuristic based
319 schedule, referred to as Quin-Modified. The MILP PAP optimization was run for 14400 seconds to a
320 non-optimal solution with a gap of 52.5% . The Quin-Modified schedule more heavily utilized the fast
321 chargers and used slow chargers more as a supplement. In sharp contrast, the MILP PAP schedule heavily
322 leaned on the slow chargers and supplemented fast chargers as needed. This can be quantified by the four
323 fast and 3 slow chargers utilized by the Quin-Modified schedule whereas the MILP PAP schedule utilized 8
324 slow chargers and 2 fast chargers. More importantly, the MILP PAP schedule utilized approximately $1 \cdot 10^5$
325 Kwh more than the Quin-Modified, but the charges remained above the constrained minimum charge of
326 25% , and charged all the buses to 70% at the end of the working day. The Quin-Modified schedule, on the
327 other hand, failed to keep all the bus charges above 0% throughout the time horizon.

328 Further fields of interest are to utilize the formulation (Eq (10) and (11)) with nonlinear battery dynamics,
329 calculation and utilization of the demand and consumption cost in the objective function, and utilizing this
330 formulation in a metaheuristic solver. Furthermore, "fuzzifying" the initial and final charge times is of
331 interest to allow flexibility in the arrival and departure times.

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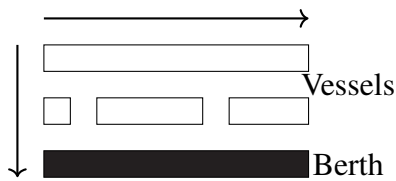
FIGURE CAPTIONS

Figure 1. Example of berth allocation. Vessels are docked in berth locations (horizontal) and are queued over time (vertical). The vertical arrow represents the movement direction of queued vessels and the horizontal arrow represents the direction of departure.
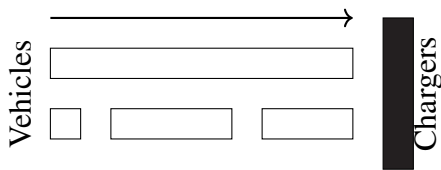

Figure 2. Example of position allocation. Vehicles are placed in queues to be charged and move in the direction indicated by the arrow.
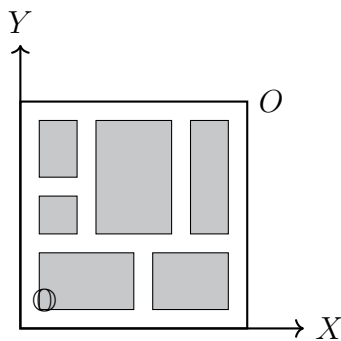

Figure 3. Example of rectangle packing problem

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Table 1. Notation used throughout the paper

| Variable	Description
Input values	
n_B	Number of buses
M	An arbitrary very large upper bound value
n_V	Number of total visits
n_Q	Number of queues
n_C	Number of chargers
$\mathbb{V}$	Set of visit indices, $\mathbb{V} = \{1, ..., n_V\}$
$\mathbb{B}$	Set of bus indices, $\mathbb{B} = \{1, ..., n_B\}$
$\mathbb{Q}$	Set of queue indices, $\mathbb{Q} = \{1, ..., n_Q\}$
i, j	Indices used to refer to visits
b	Index used to refer to a bus
q	Index used to refer to a queue
Problem definition parameters	
Γ	$\Gamma : \mathbb{V} \to \mathbb{B}$ with Γ_i used to denote the bus for visit i
α_i	Initial charge percentage time for visit i
β_i	Final charge percentage for bus i at the end of the time horizon
ϵ_q	Cost of using charger q per unit time
Υ	$\Upsilon : \mathbb{V} \to \mathbb{V}$ mapping a visit to the next visit by the same bus with Υ_i being the shorthand.
κ_b	Battery capacity for bus b
λ_i	Discharge of visit over route i
ν_b	Minimum charge allowed for bus b
τ_i	Time visit i must depart the station
ζ_b	Discharge rate for bus b
a_i	Arrival time of visit i
i_0	Indices associated with the initial arrival for every bus in A
i_f	Indices associated with the final arrival for every bus in A
m_q	Cost of a visit being assigned to charger q
r_q	Charge rate of charger q per unit time
Decision Variables	
δ_{ij}	Binary variable determining temporal ordering of vehicles i and j
η_i	Initial charge for visit i
σ_{ij}	Binary variable determining the queue ordering between vehicles i and j
c_i	Ending charge time for visit i
g_{iq}	The charge gain for visit i from charger q
p_i	Amount of time spent on charger for visit i
u_i	Starting charge time of visit i
v_i	Assigned queue for visit i
w_{iq}	Binary assignment variable for visit i to queue q
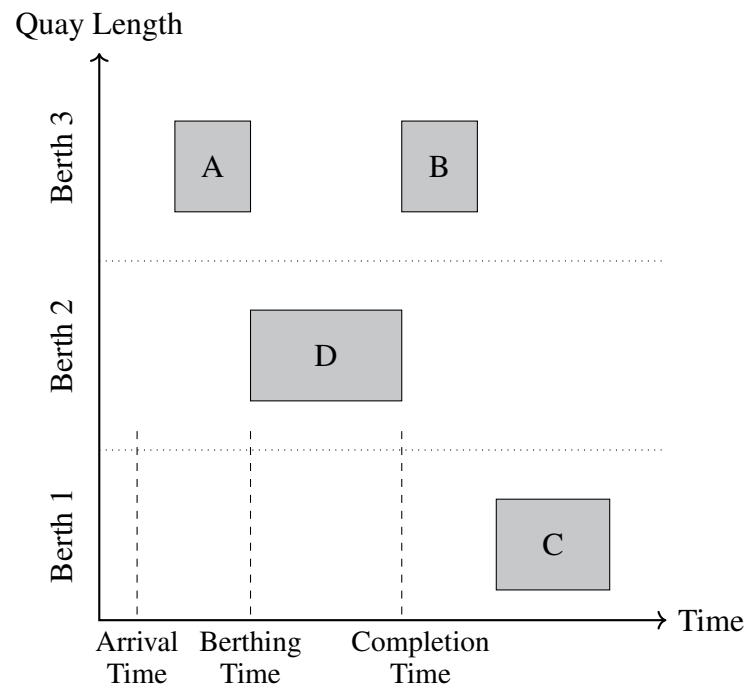
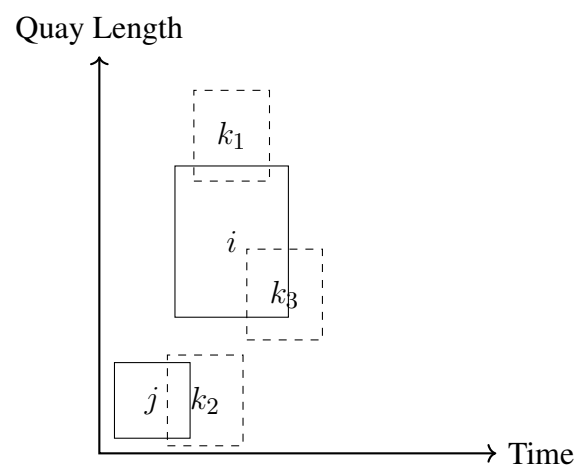**Figure 4.** The representation of the berth-time space

Figure 5. Examples of different methods of overlapping. Space overlap: $v_{k_1} < v_i + s_i \therefore \delta_{k_1 i} = 0$. Time overlap $u_{k_1} < u_j + p_j \therefore \sigma_{k_2 j} = 0$. Both space and time overlap $\sigma_{k_3 i} = 0$ and $\delta_{k_3 j} = 0$.
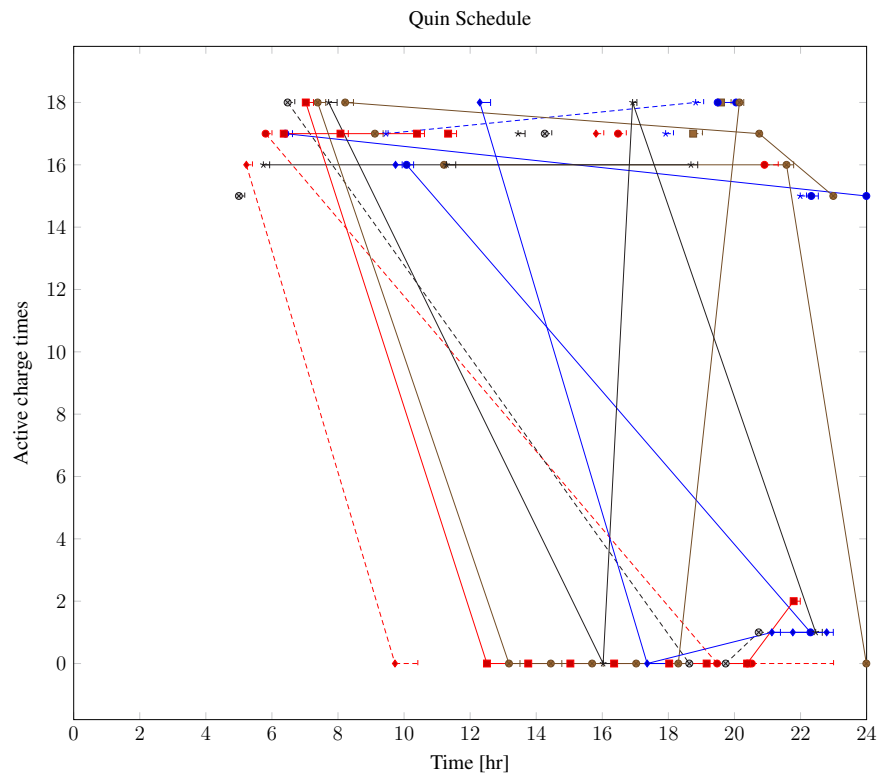
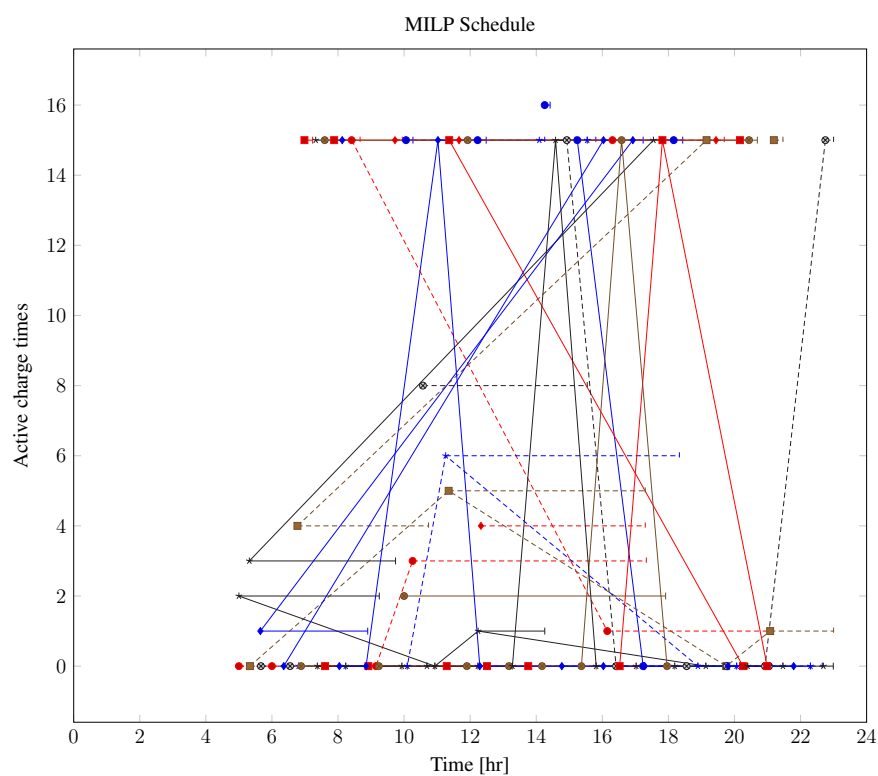**Figure 6a.** Charging schedule generated by Quin Modified algorithm.

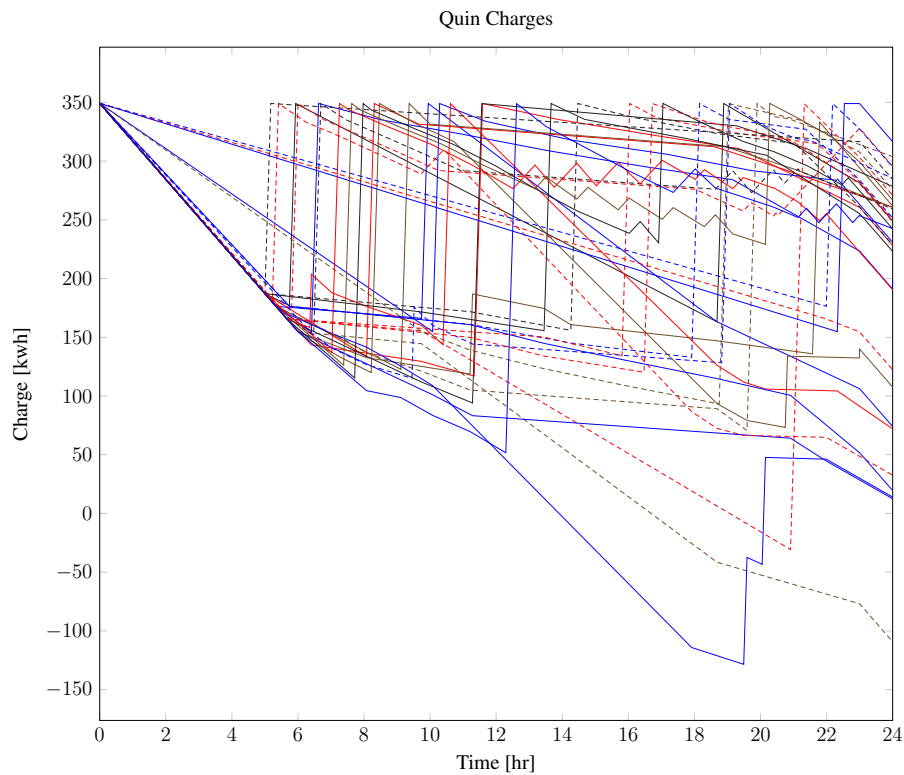

Figure 6b. Charging schedule generated by MILP PAP algorithm.

Figure 7a. Bus charges for the Quin Modified charging schedule. The charging scheme of the Quin charger is more predictable during the working day.
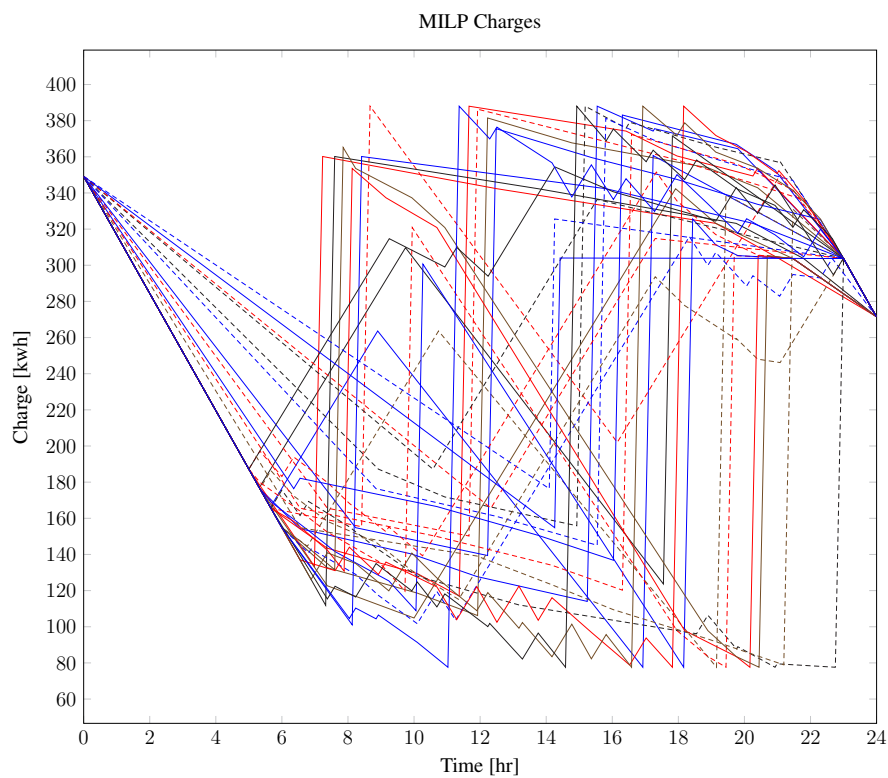
Figure 7b. The bus charges for the MILP PAP charging schedule. The MILP model allows for guarantees of minimum/maximum changes during the working day as well as charges at the end of the day.
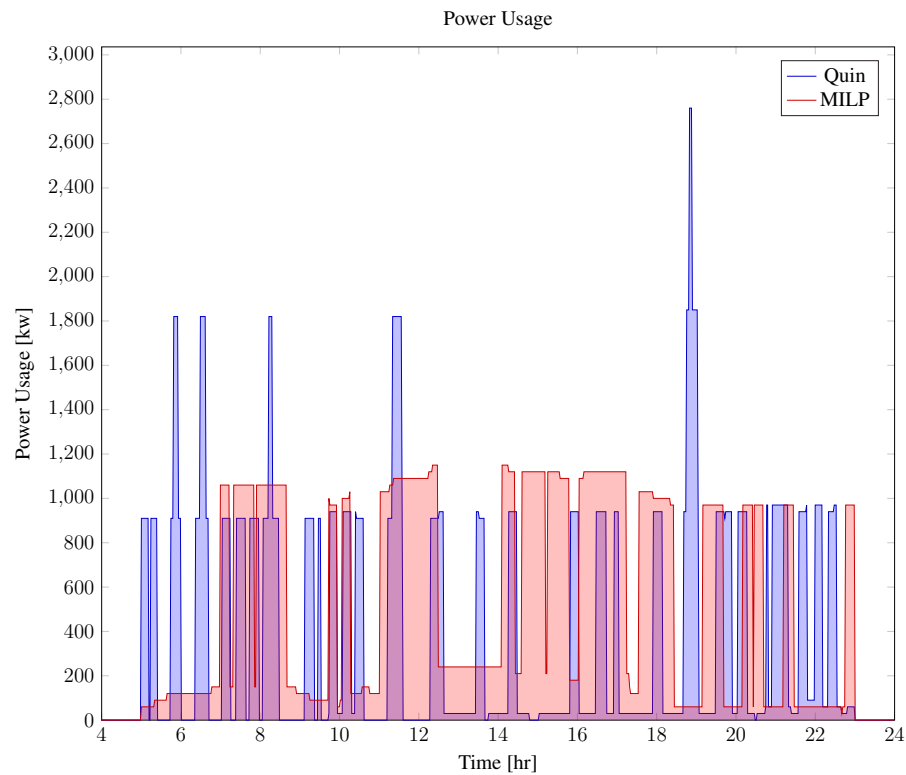
Figure 8. Total accumulated energy consumed by the Quin-Modified and MILP schedule throughout the time horizon.
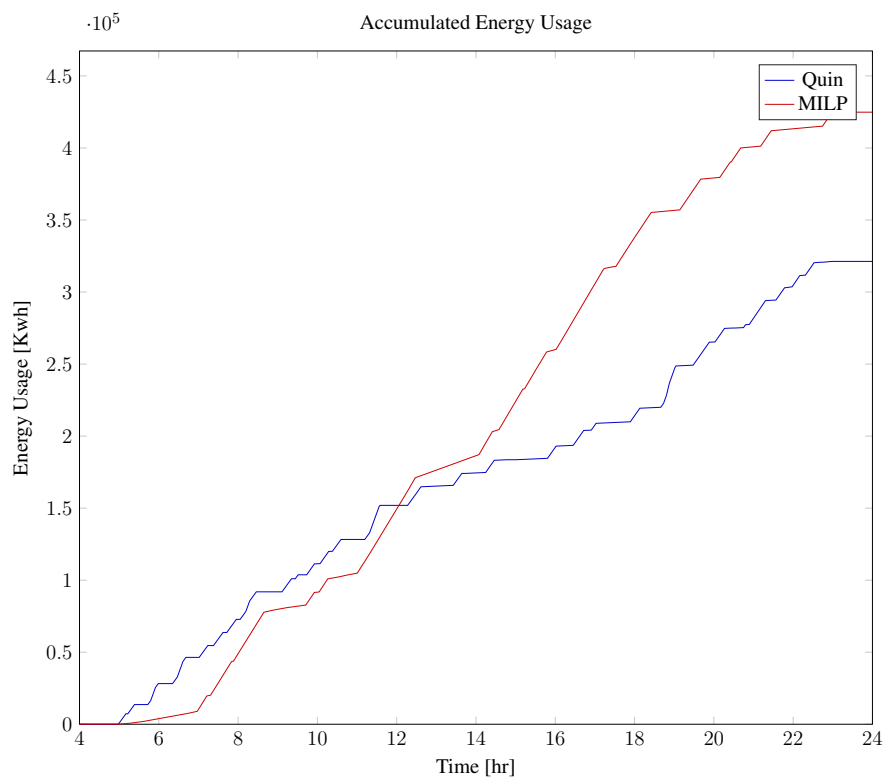

Figure 9. Amount of power consumed by Quin-Modified and MILP schedule over the time horizon.
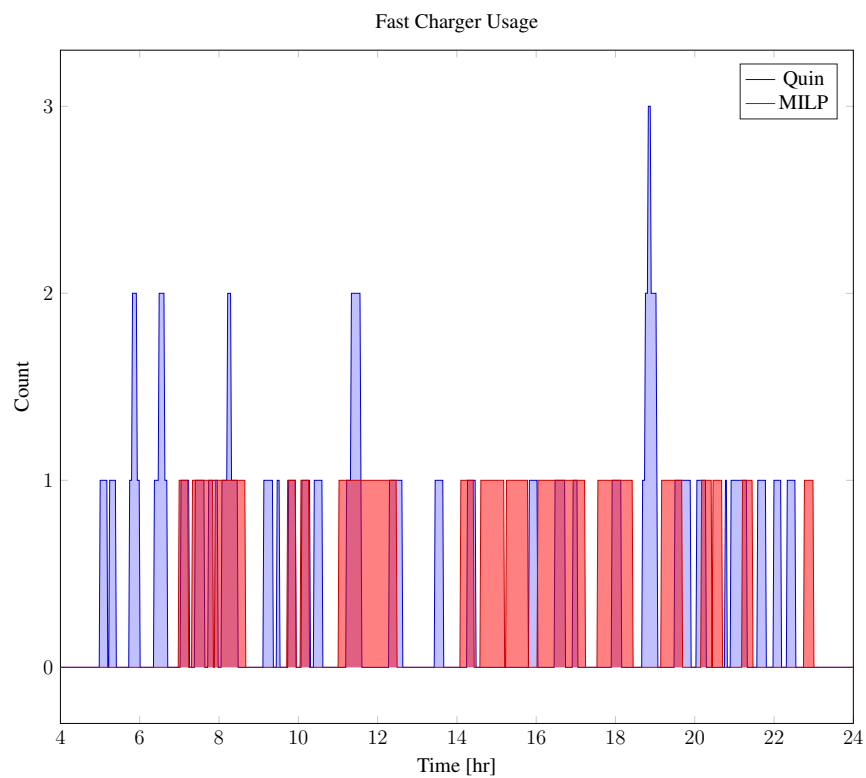
Fast Charger Usage

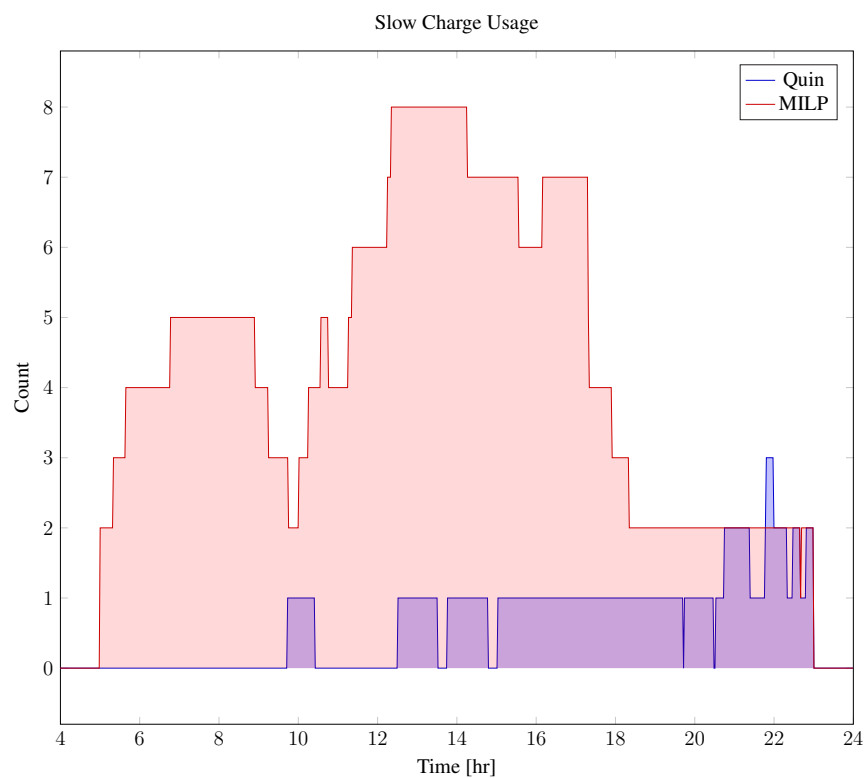**Figure 10a.** Number of fast chargers for Quin and MILP PAP.

Slow Charge Usage

Figure 10b. Number of slow chargers for Quin and MILP PAP.