Daniel's Super Cool and overly long title

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***Abstract*—TODO: add abstract**

***Index Terms*—TODO: Add Keywords**

I. Introduction

The goal of public transportation is to provide transit services using cost effective and environmentally sound methods. Most public transportation systems include bus fleets where each bus traverses a route and ferries costumers between stops. This business model puts significant miles on the buses and while effective, has several drawbacks including maintenance costs and emissions. To help overcome these challenges, many transit authorities have begun adopting electric buses which, in addition to zero emissions also offer fewer maintenance costs, and access to renewable energy[14].

Electric buses however are not without problems of their own. When an electric bus refuels, it draws power and induces a load on electrical infrastructure known as 'the grid'. The loads introduced by bus charging are substantial and can significantly increase the grid's maximum power draw[16][6][3]. The increase in maximum draw can cause additional maintenance and expense for power companies.

To recover these expenses, power companies bill more for high power use. They include charges for the maximum average power, or a 'demand' charge. They also designate high use periods as 'on-peak' and bill increased rates for energy and power. In the end, high loads are expensive for both power providers and transit authorities and can make large-scale bus charging cost prohibitive.

One approach to managing charge costs, is to plan when and how much power will be drawn. However, developing charge plans is complex and must work around route schedules, account for charge time, ensure sufficient battery charge, and consider differences between operation and offline hours. In short, the solution must consider all aspects of the bus's day to day activities.

When a bus starts the day, it has a route and schedule assigned which tells the bus operator where to be and when to be there. Throughout the day, the bus returns to the hub to pick up passengers and recharge.

Because the number of fast-chargers is limited, a bus may only charge if a charger is available and must leave on route as scheduled. Furthermore, because batteries may require several hours for a full charge, they may not have time finish. Lower charge rates may also be used for less power draw which further delays charge times.

At the end of operation hours, each bus is stored in the bus depot and connected to a 'slow' charger. Slow-charging is preferable when possible because it draws less instantaneous power and prolongs battery life [9]. Furthermore, charging during off-hours offers each bus the opportunity to charge at any time with no contention for charging resources. The buses reside in the bus depot until the next morning when they depart to run routes.

To maintain the bus battery state of charge in a nominal operations environment, there are several factors to consider including route schedules, on/off peak hours, additional grid loads, and the charge needs of individual buses. Finding a fiscally optimal charge schedule is refered to hereafter as the 'charge problem' and is the focus of this paper.

The remainder of this paper is organized as follows: Section II gives a description of previous work for solving the charge problem and Section III describes the directed graph framework used for describing the operations environment. Section IV extends the content of III to multi-graph solutions, and Section V describes a set of linear constraints that describe the battery charge dynamics. Sections VI and VII describe the rate schedule used for billing and how this is frased as an objective function to minimize. Finally, Sections VIII, IX, and X briefly describe the optimization software used to solve the mixed integer linear program as developed in previous sections, present results, and describe future work.

II. Literature Review

We acknowledge the existance of additional contributions, such as minimizing costs for startup infrastructure [17], and preserving battery lifespan [9]. However, as these are not relevent to this work, we consider them outside the scope of this review. We further acknowledge that some works cited herein contain solutions to several of these problems, such as in [20], but for sake of organization, we list them in the most relevent context.

A. Battery Charging

Here we consider solutions to empty batteries and focus our attention on either battery replacement or charging methods. We also refer to charging methods as either static (at rest) or dynamic (in motion).

Because charge times can significantly complicate logistics, [19] and [11] give methods for exchanging spent with charged batteries. The benefits include minimal down time as refueling can occur in a matter of minutes. Unfortunately, batteries can be cumbersome, and their exchange can be difficult. It also requires specialized tools, and could require automation.

Another alternative is to inductively charge buses while they traverse their routes [2], [11], [12], [5]. Unfortunately, this requires significant infrastructure which may not be available and is cost prohibitive for large systems.

Alternative solutions tend towards optimal planning. This allows for buses to charge in the traditional sense, minimizes additional infrastructure, and avoids the complexities of exchanging batteries. These approaches generally fall into one of three categories; reactive, hybrid, and global.

Reactive planning focuses strictly on presential circumstances. Methods of this type are computationally efficient, run in real-time, and are adaptable. These techniques generally stem from control theory and minipulate a current state to minimize cost. One such example includes the work done by [4], who uses comparable methodology to reduce demand on the power grid. This methodology however, does not account for global phenomena that require broader planning schemes and for the most part this class of technqiues remain unused for bus charging.

Another class of algorithms encompasses a limited number of projected events to improve decision making. This allows for a middle ground between simplicity and global planning and has proven useful in previous work [10], [1].

Global planning algorithms assume comlplete foreknowledge of future events and provide globally optimal plans [18],[7]. This class of algorithm requires more computation and is less flexible then reactive or hybrid approaches. However, the solutios are globally optimal and derive from insight unavailable to other algorithm classes.

B. Cost Management

The final set of constraints aim to decrease load on the grid. Previous work has shown that the use of electric buses can significantly complicate local power management [3] [6]. Additinally, power demand generally increases the fiscal cost from a billing perspective. [8] has provided methodology for forcasing the load on the grid. These types of models often form the basis for power distribution algorithms. For example, [15] gives an approach to minimize grid demand, but requires foreknowledge of uncontrolled loads. [4] takes a different approach and observes real-time data to control the charge rates of connected buses. [13] also operates in the real-time sense but uses on-board batteries to mitigate the effects of rapid charging.

III. Graph Based Problem Formulation

A solution to the bus charge problem must reveal *what* to charge and *when* to charge it. This implies a two dimensional solution where each axis describes *what* and *when* to charge respectively. The first dimension contains one charge state for each bus and an additional 'no-charge' state. The time axis is continuous by nature and is represented discretly by the time indices $t_0, t_1, \dots, t_n$

The intersection of each charge state and time index is represented by a node (see figure 1a) where the the ij^{th} node represents the i^{th} charge state at the j^{th} time index. For example, $\text{node}_{1,1}$ of figure 1a represents a state where a charger charges Bus 2 at time index t_0.

Note that a complete grid, implies that each charger can charge any bus at any time. When buses leave the station for routes however, they become unavailable. To reflect the various absenses caused by running routes, charge nodes corresponding to route times must be removed (see figure 1b).

Additionally, charge nodes are only valid for small periods of time. As time progresses, chargers must transition from state to state. These state transitions are represented by forming a weighted connection, or edge between two nodes (see figure 2). Each edge leaves a previous state and enters a target state. The use of each edge is determined by its weight, which gives the number of chargers using the transition. Therefore edges by themselves represent *potential* transitions (see figure 3), and are made 'active' by assigning a non-zero weight.

Edges can also be thought of as decisions because they determine the next state for each charger. In the bus charge problem, there are four types of decisions: Connect, Charge, No-Charge, and Disconnect. Connect edges are formed when an edge transitions from a no-charge state to a charge state, charge edges are given by connections from one charge state to another, No-Charge transitions occur between no-charge nodes, and disconnect edges transition from charge to no-charge states (see figure 4).

Consider a two-charger scenario where buses follow the schedule given in figure 3. A solution where Bus 1 charges from t_1 to t_2 and Bus 2 charges from t_4 to t_5 would be expressed by assigning non-zero weights to the appropriate connect, charge, and disconnect edges as shown in figure 5. Thus, solving the bus charge problem becomes a matter of finding the optimal set of edge weights.

To find the optimal set of weights, the graph must first be encoded in an incidence matrix. An incidence matrix organizes relationships between nodes and edges by describing which edges depart from and connect to which nodes. An incidence matrix A is an nNode $\times$ nEdge matrix where nNode is the number of nodes, and nEdge is the number of edges.

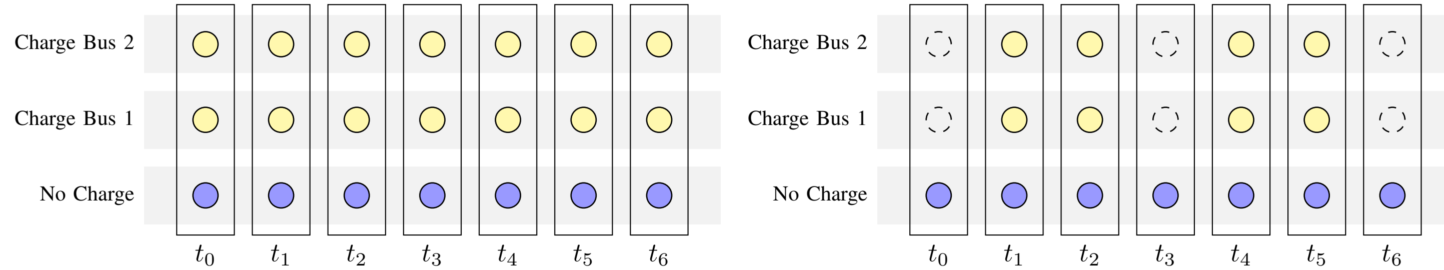
The columns of A describe connections for each edge and the rows give connections for each node. Incoming connections are represented with 1, outgoing connections with -1, and no connection with 0. For example, the graph in figure 6 can be represented as:

$$\begin{bmatrix} -1 & 0 & -1 & 1 & 0 \\ 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & -1 \\ 0 & 1 & 1 & 0 & 1 \end{bmatrix} \tag{1}$$

An incidence matrix can be used to find the number of chargers entering and leaving each state. None of the states (charging/non-charging) can create or destroy chargers and so the number of incoming must always equal the number of outgoing chargers. The only exception occurs at *source* and *sink* nodes.

A source node represents the beginning state of all chargers. Because a source state is the first, there are no incoming edges and hence, the net difference between incoming and outgoing chargers, or *the net-flow*, will be minus the number of chargers.

Sink nodes represent the final state, where all chargers enter and finish (see figure 7). Because sinks have no outgoing edges, they maintain a positive net-flow equal to the number of chargers. Let x be a vector representing the edge weights, A be an adjacency matrix, and f be a vector where f_i gives



(a) Graph showing buses and timesteps

(b) two-bus scenario from figure 1a where each bus is absent at t_0, t_3, and t_6

Fig. 1: Bus availability represented in a graph

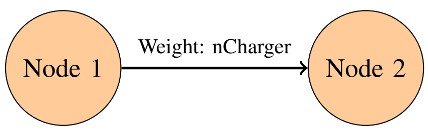


Fig. 2: Node to Node Connection

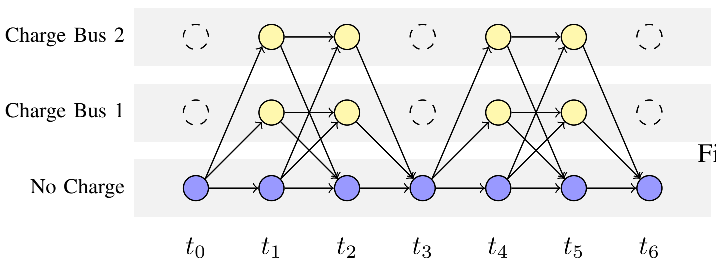


Fig. 3: Complete Problem formulation

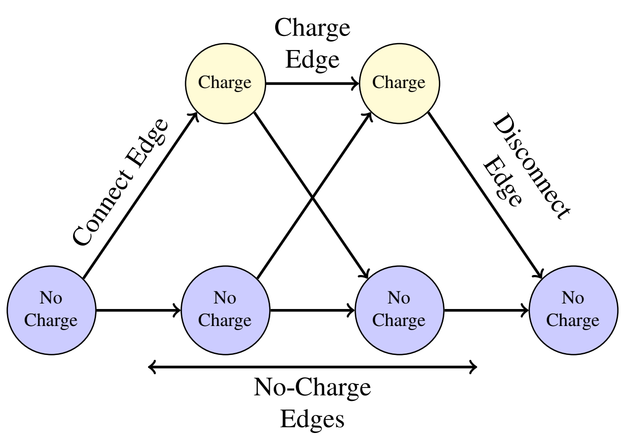


Fig. 4: Connect, Disconnect, and Charge Edges

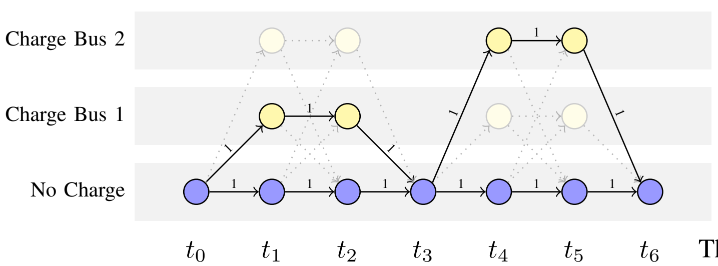


Fig. 5: One solution to a 2-bus 2-charger scenario

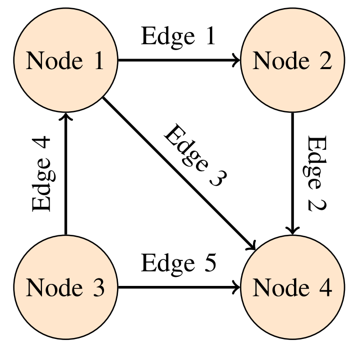


Fig. 6: A generic directed graph consisting of nodes and edges

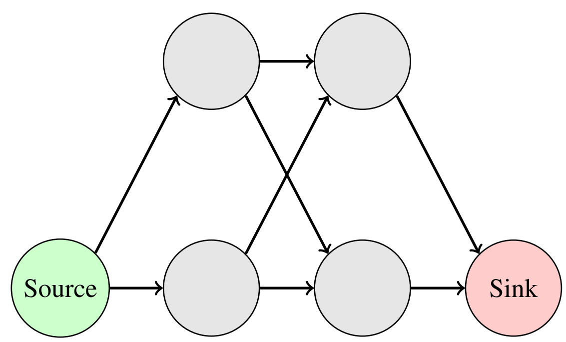


Fig. 7: Network flow illustrating sources and sinks

the net-flow for the i^{th} node. The net-flow for each node can be expressed as

$$Ax = f \tag{2}$$

This expression can be used to constrain the net-flow of each node. f must equal zero for all non-source and non-sink elements and source/sink nodes must have net-flows equal to

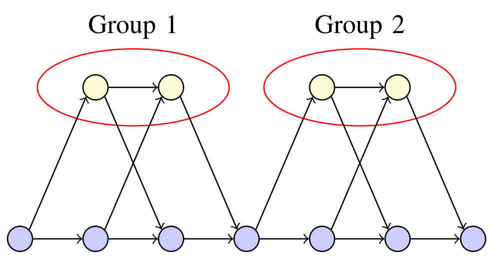


Fig. 8: Example of groups in a network flow graph

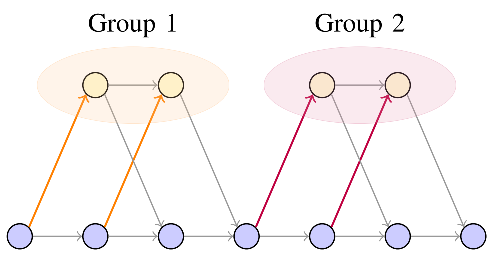


Fig. 9: Incoming Group Edges

−nChargers and nChargers respectively (see equation 3).

$$Ax = \begin{bmatrix} 0 \\ \vdots \\ -\text{nCharger} \\ \vdots \\ 0 \\ \text{nCharger} \\ \vdots \\ 0 \end{bmatrix} \tag{3}$$

Flow can also be used to ensure that buses connect to only one charger at a time. Let a charge session, or *group*, be the set of all charge nodes between routes as shown in figure 8. The *group flow* is the number of chargers that enter a group and is computed by adding the weights for all incoming edges (see figure 9).

Let B be a nGroup $\times$ nEdge matrix where the ij^{th} entry is 1 if the j^{th} edge enters the i^{th} group and 0 otherwise. For example, the B matrix corresponding to figure 10 contains 1 in the 7^{th} and 10^{th} columns for Group 1, and 12^{th} and 15^{th} columns for group 2 as given in equation 4.

$$B = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \end{bmatrix} \tag{4}$$

The group flow is then computed as

$$Bx = \text{Group Flow}. \tag{5}$$

But the group flow is required to be one at most. This is expressed by the inequality given in equation 6.

$$Bx \leq \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}, \tag{6}$$

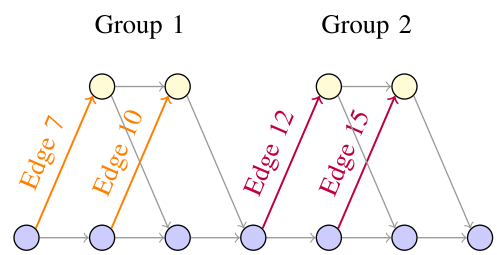


Fig. 10: Connect edge example for groups

where x is a matrix giving the number of chargers traversing an edge, and B describes all mount edges (see figure 4) corresponding to the same group. In B, the i,jth value is one if the jth edge mounts to the ith group. For example, the graph given in figure 10 would have the following group constraints:

IV. Multi-Graph Additions

An additional contribution this work offers is the expansion to night vs day charging. During the night, there is one charger for each bus; each with a single charge rate. During this time, buses are also available to charge at any time. These differences in operations introduce changes to the original graph formation and warrent a separate graph.

Night graphs consider a situation where both the number of buses reflecte the number of chargers and buses are readily available. Note how there are several source and sink nodes in figure 11. When a bus deploys for the day, the available number of charges changes and are reflected in the underlying source and sink constraints.

Changes in the first graph are reflected in the second through use of state of charge variables.

V. Battery State of Charge

The state of charge (SOC) is influenced in three ways; initial conditions, discharge events, and traversing charge nodes (as shown in figure 4). There are SOC variables for each node representing an available bus, where the SOC value for the ith bus at SOC index j is denoted as $d_{i,j}$ as shown in figure 12. Note, there only needs be SOC variables for time indices where buses are available to charge and $d_{i,j}$ does not generally correspond to the charge at *time interval* j. All other timesteps are deterministic and need not be computed.

When charging, the change in SOC associated with the ith bus at the jth charge edge is denoted $g_{i,j}$. Again, note that j is *not* indicative of a time interval, rather it gives the *index* of the *charge edge* in use as shown in figure 13.

An additional contribution this paper gives is the addition of multi-rate charging. This adapts the basic methodology to incorporate additional charge edges and $g_{i,j}$ variables. Under this methodology, the graph given in figure 8 would be modified to reflect figure 14, where $g_{i,j,k}$ represents the ith bus at charge instance j and charge rate k.

To model the effect of charging on a battery state of charge, we adopt the Constant Current Constant Voltage (CCCV) model as derived in [18] which gives

$$s_{k+1} = \bar{a}_l s_k - \bar{b}_l M \tag{7}$$

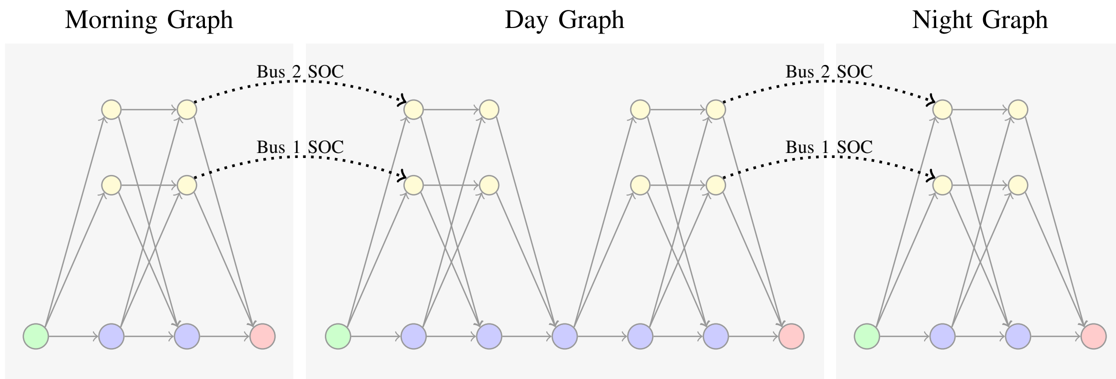


Fig. 11: Night vs Day Graphs

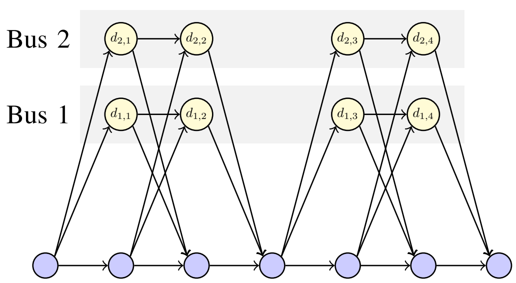


Fig. 12: SOC indicators

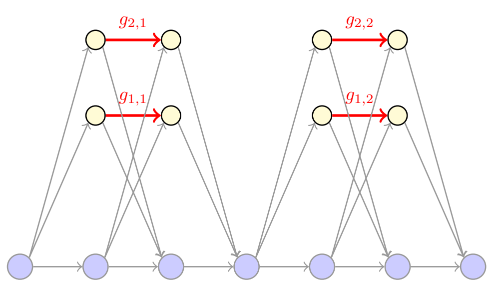


Fig. 13: Depiction of which edges increase SOC for the single rate case

Where s_k is the charge of a battery at time k, $\bar{a}_l$ is a charge rate dependent, experimentally determined value, $\bar{b}_l = \bar{a}_l - 1$, and M is the maximum capacity of the battery in kWh.

Recall how g represented the change in state of charge of the battery in kWh. This allows us to express s_{k+1} in terms of

$$s_{k+1} = s_k + g_{\pi_g(m,k,l)} \tag{8}$$

where $\pi_g(m,k,l)$ represents the index of g for bus m at time

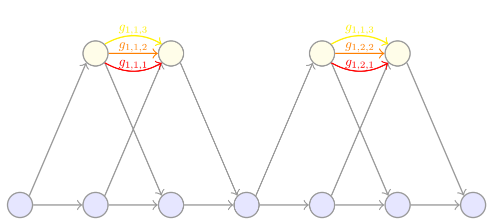


Fig. 14: Multi-Rate Charging

index k for charge rate l. These two equations imply that

$$\begin{aligned} s_k + g_{\pi_g(m,k,l)} &= \bar{a}_l s_k - \bar{b}_l M \\ \Rightarrow g_{\pi_g(m,k,l)} &= \bar{a}_l s_k - s_k - \bar{b}_l M \\ \Rightarrow g_{\pi_g(m,k,l)} &= s_k(\bar{a}_l - 1) - \bar{b}_l M. \end{aligned} \tag{9}$$

But the state of charges for bus m are given in terms of $d_{i,j}$. If we let $d_{i,j} = \pi_d(i,k,l)$, then the final expression for g becomes

$$g_{\pi_g(m,k,l)} = d_{\pi_d(m,k,l)}(\bar{a}_l - 1) - \bar{b}_l M. \tag{10}$$

Note, 10 is only valid when the bus is charging and must be tempered with additional constraints to account for the non-charging case.

To handle the two cases, we express the cases for charging (equation 10 and non-charging ($g = 0$) as

$$\begin{aligned} g_{\pi_g(m,k,l)} &= d_{\pi_d(m,k,l)}(\bar{a}_l - 1) - \bar{b}_l M \\ g_{\pi_g(m,k,l)} &= 0. \end{aligned} \tag{11}$$

which also implies that

$$\begin{aligned} g_{\pi_g(m,k,l)} &\le d_{\pi_d(m,k,l)}(\bar{a}_l - 1) - \bar{b}_l M \\ g_{\pi_g(m,k,l)} &\ge d_{\pi_d(m,k,l)}(\bar{a}_l - 1) - \bar{b}_l M \\ g_{\pi_g(m,k,l)} &\le 0 \\ g_{\pi_g(m,k,l)} &\ge 0. \end{aligned} \tag{12}$$

Next, let $x_{\pi_x(m,k,l)}$ be the index of the edge corresponding to $g_{\pi_g(m,k,l)}$. A switch between the two constarints expressed in equation 12 can be constructed using the *big M* technique. This modifies equation 12 such that

$$\begin{aligned} g_{\pi_g(m,k,l)} &\le d_{\pi_d(m,k,l)}(\bar{a}_l - 1) - \bar{b}_l M - M(1 - x_{\pi_x(m,k,l)}) \\ g_{\pi_g(m,k,l)} &\ge d_{\pi_d(m,k,l)}(\bar{a}_l - 1) - \bar{b}_l M \\ g_{\pi_g(m,k,l)} &\le 0 + M x_{\pi_x(m,k,l)}) \\ g_{\pi_g(m,k,l)} &\ge 0. \end{aligned} \tag{13}$$

Note that as expressed, when the charge edge is active (i.e. $x_{\pi_x(m,k,l)} = 1$), then

$$\begin{aligned} g_{\pi_g(m,k,l)} &\le d_{\pi_d(m,k,l)}(\bar{a}_l - 1) - \bar{b}_l M \\ g_{\pi_g(m,k,l)} &\ge d_{\pi_d(m,k,l)}(\bar{a}_l - 1) - \bar{b}_l M \\ g_{\pi_g(m,k,l)} &\le M \\ g_{\pi_g(m,k,l)} &\ge 0. \end{aligned} \tag{14}$$

Bus as g can never exceed the charge capacity of the battery, the bottom two constraints are inactive and g is both less than or greater than equation 10, making it equal. When the edge is inactive, or $x_{\pi_x(m,k,l)} = 0$, equation 13 becomes

$$\begin{aligned} g_{\pi_g(m,k,l)} &\leq d_{\pi_d(m,k,l)}(\bar{a}_l - 1) - \bar{b}_l M - M \\ g_{\pi_g(m,k,l)} &\geq d_{\pi_d(m,k,l)}(\bar{a}_l - 1) - \bar{b}_l M \\ g_{\pi_g(m,k,l)} &\leq 0 \\ g_{\pi_g(m,k,l)} &\geq 0. \end{aligned} \tag{15}$$

where the top two constraints become inactive and g is both less than and greater than 0, making it equal. Hence, these constraints can be expressed in linear form as

$$\begin{aligned} -g_{m,k,l} + d_{m,k,l}(\bar{a}_l - 1) + x_{m,k,l} &\leq M(\bar{b}_l + 1) \\ g_{m,k,l} - d_{m,k,l}(\bar{a}_l - 1) &\leq -\bar{b}_l M \\ g_{m,k,l} - M x_{m,k,l} &\leq 0 \\ -g_{m,k,l} &\leq 0. \end{aligned} \tag{16}$$

The constraints for state of charge are circumstantially dependent. Each $d_{m,k,l}$ must be defined by a set of constraints which are defined by either initial conditions, previous graphs, route discharge, or $g_{m,k,l}$ variables.

Initial conditions and previous graphs are straight forward. Initial conditions are given as an equality constraint. For example, if d_0 was initialized to 80 kWh, the constraint would be $d_0 = 80$. To initialize to the value of a previous graph, use an equality constraint.

Suppose we modeled early morning and day-time operations and had two corresponding graphs. The final node of graph one would be equivalent to the first node of graph two in the temporal sense and the corresponding $d_{m,l,k}$ values would also be equated as $d_{\text{Graph 1}} - d_{\text{Graph 2}} = 0$.

$d_{m,l,k}$ values corresponding to available charge times are expressed as a sum of $g_{m,k,l}$ values given in equation 16 such that

$$d_{m,k+1} = d_{m,k} + \sum_l g_{m,k,l}$$

or as given in linear form,

$$d_{m,k+1} - d_{m,k} - \sum_l g_{m,k,l} = 0. \tag{17}$$

The final case deals with battery discharge over a route. As seen in figure 15, discharge values, also refered to as δ represent the power expenditure overa route. This expenditure is modeled as a withdrawel from the resevour in a battery and was calibrated from data received from the Utah Transit Authority. In figure 15, the SOC constraints corresponding to δ_1 would be as follow:

$$d_{1,3} = d_{1,2} - \delta_1$$

or in linear form,

$$d_{1,2} - d_{1,3} = \delta_1. \tag{18}$$

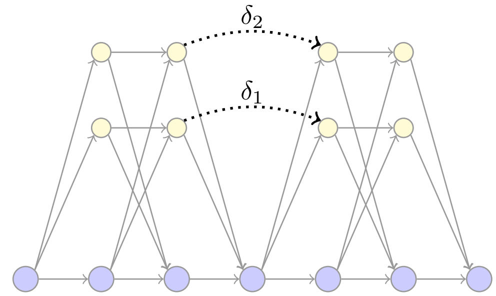


Fig. 15: δ values for routes

VI. Fiscal Rate Schedule

One objective of this work is to minimize the fiscal cost associated with power use and uses the Rocky Mountain Power schedule 8 billing rates. This billing schedule includes an on-peak power charge, facilities charge, and both on and off peak energy charges.

The facilities charge is computed by calculating the average power over a 15 minute period. The facilities charge is based on the maximum average value over the course of the month. This section of the bill charges \$4.81 per kW. The On-Peak Power Charge is similarly calculated but only includes average values from designated on-peak hours. Rocky Mountain Power charges \$15.73 per kW for this value.

the facilities power can be formulated as a linear set of constraints that include power used at each timestep for charging buses and external loads. This can be expressed as

$$c_i = \sum_j g_{i,j} + p_i$$

Where c_i represnets the

The energy charges are billed per kWh and charge for each unit of energy used. There are two rates: 5.8282¢for energy consumed during on-peak hours, and 2.6316¢for off-peak hours. general introduction with details for demand and consumption charge and how these relate to the end-of-the-month billing.

a. external loads (contribution) b. consumption charge i. total energy in Kwh ii. on-peak vs off-peak iii. constraints for consumption charge c. demand charge i. average power in 15 minute window ii. on-peak vs facilities iii. constraints for on-peak and facilities charges d. total cost breakdown i. Show how Rocky Mountain Power uses these and what the cost weighting is.

VII. Bus Fleet Operations

Overview of bus operations during the day vs the night a. night environment i. one charger per bus ii. slow chargers iii. single rate chargers iv. buses always available b. day environment i. limited number of chargers ii. fast/variable rates iii. limited charging availability c. multiple graphs to incorporate day vs night charging i. show picture to illustrate this ii. show SOC constraints to implement these relationships

VIII. Objective Function

IX. Gurobi & Usage

X. Results

XI. Future Work

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