EMPOWERING ELECTRIC BUS DEPLOYMENT WITH STANDARDIZED TRANSIT DATA

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ABSTRACT

This study evaluates the accuracy of bus energy consumption estimates built on GPS data sampled at low frequencies as collected from standardized transit data feeds. It applies bus travel time forecast models to generate drive cycles for buses in any network reporting standardized data. An energy model is then applied to 33 international bus networks to examine needs for implementing battery electric buses. Prior work on this topic has focused on aggregating standardized bus GPS data directly to route segments. This study instead uses trained models to impute speed profiles for routes and networks without requiring collection of network-specific data beyond that published in standard data feeds. This allows a wider-reaching comparison of agency electrification needs. Sensitivities are tested for key operational factors. Conclusions are then drawn on the adequacy of standardized bus data for energy analysis, and practical findings across agencies. Findings suggest that low sampling frequency feeds do not significantly impact energy consumption estimates for battery electric buses, despite the challenges of modeling vehicle drive cycles. Current battery and charging technology is capable of supporting initial rollouts with unmanaged charging on low-energy scheduling blocks, but incapable of supporting full electrification. To mitigate peak power costs and meet energy needs under full electrification scenarios, it is essential for agencies to adopt managed charging strategies.

Keywords: Battery Electric, Bus, Drive Cycle, Energy, GTFS-RT

INTRODUCTION

Motivation

Open source data and tools enable novel workflows that do not have industry established toolsets. They encourage a collaborative development process that helps in sharing knowledge for research and practice. For example, the electrification of bus networks poses common challenges to many agencies, which could be efficiently addressed with shared tools.

There are several benefits to bus electrification. Foremost, it reduces operating costs for maintenance and fuel (*1*). This is a key benefit given the operations funding shortfalls currently facing transit agencies (*2*). From a greenhouse gas (GHG) emissions standpoint, electrification of bus fleets is less important than personal vehicles, as they only account for 1.3% of annual emissions (*3*). However, diesel engines used in many fleets produce high concentrations of unhealthy criteria air pollutants (CAP) (*4, 5*). Reducing noise pollution from diesel buses also improves quality of life for residents residing near transit corridors, and improves passenger experience riding transit (*6, 7*).

There are barriers that must be addressed before these benefits can be realized. The capital investment to transition to electric transit includes purchasing vehicles that are currently more expensive than diesel counterparts (*1*), though that is expected to change in the near future as battery manufacturing improves and supply chains stabilize (*8*). It also requires investment in charging infrastructure and facilities to maintain electric buses. There are also personnel costs for training or hiring workers skilled in operating and maintaining electric buses. All told, there is a significant capital expenditure to reach full fleet electrification, despite cost savings over the life of each vehicle.

Thus, fleet electrification projects currently require federal funding to be cost-effective. When funding through programs such as the Low or No Emission Vehicle Program (*9, 10*) cover 80% of vehicle purchasing costs, a typical battery electric bus (BEB) has a lifecycle cost up to 23% lower than diesel or compressed natural gas counterparts (*11*). Despite this, there are a large number of variables regarding vehicle operation, charging strategy and interaction with utilities' power distribution infrastructure that can greatly influence the cost of implementing BEBs.

Furthermore, there is very little real-world knowledge on designing and operating BEB fleets relative to the variety of possible implementations. As of 2023, only 2% of all bus transit was electric (*12*) and 44% of transit agencies could not envision a path to full fleet electrification (*12*). This creates an opportunity for open source, generalizable bus fleet electrification planning tools that can be used by agencies to make informed decisions on their transition to BEBs.

Outline of This Work

This study addresses agency uncertainties surrounding infrastructure needs for fleet electrification. It first examines the accuracy of energy consumption estimates from low resolution open data to a set of validation data collected with a phone and global navigation satellite system (GNSS) receiver. It then applies the generative models developed in (*13*) to impute driving cycles built on General Transit Feed Specification–Realtime (GTFS–RT) data. These use standardized bus data sources such that the analysis is replicable for any agency or location, which is demonstrated by extending the analysis to 33 bus networks. The generative models use features of the built environment, static transit feed, and a small sample of realtime data to generalize travel time forecasts for any transit network. The sensitivity of energy consumption estimates and design implications to key factors such as auxiliary power, passenger load, and driver behavior are tested across all net-

works. Conclusions are then drawn on the adequacy of tools built on open standardized transit data for predictive energy modeling and practical findings for transit agencies transitioning to BEBs.

LITERATURE REVIEW

Battery Electric Bus Design Space

The primary components of a BEB system are vehicles and chargers. While vehicle chassis and maintenance equipment can be adapted for BEBs, they don't significantly influence system design. The vehicle's range is its main design variable, while location and maximum power are crucial for chargers (*1*).

BEB charger types include infrastructure-mounted cross rail, vehicle-mounted pantograph, enclosed pin/socket, and wireless inductive connections (*14, 15*). Charging power ranges from 50 to 1,000 kW, with cross rail and pantograph offering the highest rates, and plug-in and inductive generally slower (*15*). Chargers must typically connect to the grid, though off-grid power storage is possible. Charger locations vary from route ends, individual bus stops, to central depots, with each connection type having specific advantages and disadvantages. Choosing a charging strategy requires understanding vehicle energy consumption and range in real-world use.

Usable vehicle range depends on energy consumption and battery capacity, which comes with a weight trade-off. Unlike diesel, increasing battery capacity for more range adds significant weight, thus increasing energy consumption. Excess battery capacity beyond route needs is counterproductive. Higher charging rates generally shorten battery lifetimes, and extreme state of charge (SOC) and environmental conditions also affect battery longevity (*16*). Faster charging supports opportunistic charging, allowing smaller batteries for longer routes, while slower rates are better for overnight depot charging. Selected charging strategies and battery sizes must also consider demand charges related to peak power draws while meeting route capacity needs.

BEB energy consumption on-route is influenced by many factors. Low temperatures decrease battery efficiency and range, high heating, ventilation, and air conditioning (HVAC) loads significantly impact consumption, and stopping, idling, and accelerating at stops lead to increased energy consumption per mile (*17, 18*) even though BEBs are more efficient than diesel buses under such conditions. Uphill routes require more energy, and passenger loads interact with required acceleration energy and energy regenerated via braking. Overall speed greatly influences energy consumption due to air resistance. Slower trips with more idling also consume more energy per mile due to the influence of auxiliary loads.

The total consumed energy is then a combination of energy efficiency and power demand over time, which can be measured using a vehicle drive cycle. The vehicle drive cycle or operating profile is a map of velocity over time, which is representative of typical driving conditions for a design vehicle. This provides an estimate of route energy consumption from which one can begin to devise a charging strategy and fleet electrification plan.

Modeling Energy Consumption with GPS Data

There are many approaches to developing vehicle drive cycles. Foremost, there are standardized cycles for light duty vehicles as well as buses and other vehicles (*19*). These are collected using onboard vehicle speed sensors across a variety of driving styles and contexts. The main criticisms of standardized drive cycles are that they over-generalize and do not closely replicate real-world driving conditions or topography (*20*). This is a particular challenge for agencies switching to BEBs, as the characteristics of individual routes and even individual drivers may significantly

impact the energy and charging needs for the route and/or system. Many drive cycles for buses (and general tests of vehicle performance) are collected at the Altoona testing facility (*21*).

GPS data has been previously used to develop bus drive cycles and estimate vehicle emissions under typical conditions for specific cities or regions (*22, 23*). In these studies, onboard collection is employed to gather large quantities of drive cycle data, which is then classified according to typical times of day, route types (e.g., inter-city, within-city, peak/off hour), driving behavior, and more (*24, 25*). The exact classification criteria vary by study. In some cases, onboard data are combined with topography data from a digital elevation model (DEM) to provide a better estimate of energy consumption along specific routes (*26, 27*). In the absence of real passenger loading data, probabilistic methods can also be used to estimate vehicle loads during given trip segments (*26*).

There are fewer studies that use open data for bus drive cycle development. The main challenge with using open data sources such as GTFS–RT for drive cycle development is that they are relatively low resolution. This makes it more challenging to distinguish acceleration and deceleration events in the drive cycle. Aerodynamic resistance varies nonlinearly with speed, and acceleration generally uses more energy than can be recovered through regenerative braking. Thus low resolution data will tend to underestimate energy consumption by obscuring departures from average speeds. Even automatic vehicle location (AVL) data is of lower resolution than the onboard sensors can provide. In one study AVL was found to provide energy estimates 80-90% as accurate as those developed from onboard collected bus GPS data (*28*).

There is one prior work that used a combination of General Transit Feed Specification (GTFS) and GTFS–RT data to develop system-wide electric bus drive cycles (*29*). This study resampled the coordinates of static route shapes, then map-matched collected speed observations from GTFS–RT data to said coordinates. This gave estimates of the distribution of speed for vehicles traversing each segment, similar to the analysis used in (*30*). The prior work was calibrated against phone collected GPS data, and against a synthetic drive cycle generated from pure GTFS with scheduled target speeds and probabilistic interactions with stops and intersections. Their analysis spans two routes from the Victoria Regional Transit System in Canada.

Absent GPS data for a given bus route, a simulation model can estimate drive cycles based on assumptions for driver behavior, roadway conditions and more. A simulation approach does not require GPS data collection from individual buses. However, to achieve accurate predictions it must be calibrated using traffic counts and driver behavior. One study tested a range of assumptions for roadway Level of Service (LoS) for a single bus route and found consumption to range by 0.81 kWh/mi between low- and high-congestion scenarios (*31*).

Estimating energy consumption from a given drive cycle depends on the vehicle's physics-based power consumption model. This is a function of the vehicle's powertrain, which is a combination of the engine, transmission, and other physical components. Given a speed profile, sophisticated energy models such as NREL's Future Automotive Systems Technology Simulator (FASTSim) can be used to estimate energy consumption (*32, 33*). However, Wilson and Crawford (*29*) used a slightly simpler physics-based model that was originally built as part of a different prior work (*34*). That model accounts for gravity, acceleration, air resistance, rolling resistance and assumed static loads (e.g., HVAC) on the energy consumption.

There is one other notable study which developed a set of open source tools for estimating bus energy consumption from GTFS (but not GTFS–RT) data (*35*). That work focused on applying standardized drive cycles to static GTFS data and exploring system costs and component degrada-

tion over time. It is possibly the best example of generalizable open software in this space, given that it can be applied to any GTFS feed and is available as a python package.

Contribution of This Work

There are two main contributions of this study. The first is to the growing set of tools for bus transit design and evaluation built on standardized, open data. This study evaluates the accuracy of energy estimates developed from GTFS–RT-based drive cycles. It does so by validating the cycles against manually collected phone and GNSS receiver data. This comparison sheds light on the reliability and effectiveness of using standardized open data for predictive energy modeling. This first portion of the work draws conclusions on the potential benefits and drawbacks of using the GTFS–RT standard for energy modeling.

Building from the first contribution, the second contribution of this study is to the field of bus transit electrification analysis. This study applies generalizable travel time models developed in prior work to construct data-informed drive cycles for unseen bus routes and networks. This allows a small sample of realtime data to be leveraged for predictive drive cycle modeling, and capture more variation than using a standardized cycle across many diverse bus feeds. This analysis is then applied to a cross-section of 33 bus transit networks. The second portion of the work draws conclusions on the impact of key operational factors such as auxiliary power, passenger load, and driver behavior on energy consumption and design implications for transit agencies considering BEB adoption.

METHODS

Drive Cycle Energy Estimation

A bus drive cycle is a map of velocity over time which is representative of typical driving conditions for a design route. A drive cycle can be combined with a vehicle energy model to estimate the typical power profile and energy required to drive said design route. Fuel consumption is driven by aerodynamic, rolling resistance, gravity and acceleration forces. These forces, auxiliary loads and powertrain component efficiencies determine the total energy required for a design vehicle to carry out a specified drive cycle. Energy consumed can be converted to fuel consumption and aggregated across routes to estimate network power needs and environmental impacts.

The National Renewable Energy Laboratory (NREL) FASTSim model is a combined vehicle and energy model. It is validated against the Environmental Protection Agency (EPA) tested fuel consumption values of 700 vehicles, falling within 5-10% in all cases (*32*). Given a design vehicle and drive cycle it can estimate power over time and total energy consumption for the cycle. FASTSim has a built-in vehicle library with 62 vehicles. These include light-, medium- and heavy-duty vehicles as well as a mix of internal combustion engine vehicle (ICEV), plug-in hybrid electric vehicle (PHEV), hybrid electric vehicle (HEV) and battery electric vehicle (BEV) powertrains. In this study only the FASTSim energy estimation framework is used, but it can also estimate vehicle component lifetimes and total cost of ownership.

One additional benefit of the FASTSim model is that it can estimate the impact of road grade on energy consumption. Road grade is input to FASTSim as slope, or rise over run between consecutive drive cycle points. Road grade plays an important role in the required force for acceleration and in the amount of energy recovered by regenerative braking when decelerating. The elevation data used in this study is collected from a combination of the United States Geological Survey 3D Elevation Program (USGS 3DEP) DEM (10m resolution), the EU DEM (30m resolu-

tion) and the ALOS World 3D (AW3D) DEM (30m resolution) (*36–38*). The higher resolution USGS 3DEP is used as a first priority, with the others filling in where it is unavailable.

BEB Vehicle Design Parameters

The design vehicle for this study was based on the 2022 New Flyer XE40 BEB. The FASTSim vehicle library does not include any medium- or heavy-duty BEVs. Therefore the parameters for the design vehicle were gathered from several sources. The first and highest priority source was the Altoona bus testing report for the 2022 New Flyer XE40 (*21*). For geometric parameters not found in the report, the second source was heavy-duty diesel vehicles in the FASTSim vehicle library. The last and lowest priority source were other BEVs in the FASTSim library. These were used for parameters related to the engine map and drivetrain component efficiencies. Table 10 shows each parameter, its source and the value used in the model.

The Motor Controller (MC) parameters describe aspects of the alternating current (AC) motor used for propulsion. It is analogous to an internal combustion engine (ICE). The energy storage system (ESS) is the onboard battery used to drive the AC motor. It is analogous to a fuel tank. The bus has two axles with dual rear wheels giving six total wheels. The weight parameter includes the curb weight of the vehicle with an additional 150 lbs for the driver and each seated passenger (41 total). The auxiliary power includes heating at half-capacity and no air conditioning (the same setup as used in the Altoona test cycle (*21*)).

The Altoona testing procedure includes measured energy consumption (at the ESS) from standardized drive cycles. The drive cycles included for the New Flyer XE40 were the EPA Heavy-Duty Urban Dynamometer Driving Schedule (HD UDDS) cycle, the Manhattan cycle and the Orange County bus cycle. The tests were performed at seated weight with heat at half-capacity and no air conditioning. These cycles were used to validate the energy consumption of the bus parameters in Appendix 10. Table 1 shows the energy consumption estimated by FASTSim of the BEB vehicle model on each of the standardized cycles.

TABLE 1 Design Vehicle Energy Consumption for Standardized BEB Drive Cycles

Drive Cycle	Reported Consumption	Modeled Consumption
Manhattan	2.75 kWh/mi	2.77 kWh/mi
Orange County	2.00 kWh/mi	2.18 kWh/mi
HD-UDDS	1.99 kWh/mi	1.98 kWh/mi

These results show that the BEB vehicle model is within 10% of the reported energy consumption for each of the standardized drive cycles. It is within 1% of the reported energy consumption for the Manhattan and HD-UDDS cycles. This performance is similar to that previously reported for FASTSim on other vehicles. Of course, there are many vehicles on the market, and a different design vehicle would have different implications for efficiency. Prior work has shown that varying vehicle design parameters and ambient conditions shift efficiency from 0.69 to 3.7 kWh/mi (*39*). In this work, we use the New Flyer XE40 as a representative design vehicle.

Validating GTFS–RT Cycles with High Precision GNSS Receiver Data

One of the main challenges with using open standardized bus data for modeling energy consumption is the low resolution of these data. Drive cycles are typically reported at 1 Hz, whereas a GTFS–RT feed's update frequency can vary depending on the bus network and vehicle (typically

1/30 Hz). This study aims to address this challenge by collecting 1 Hz phone and GNSS receiver data from onboard active bus trips. Using the vehicle ID painted outside the vehicle, these high resolution data are matched to reported locations in the low resolution GTFS–RT data. Using FASTSim, energy estimates from drive cycles built on these data can be compared to those built on GTFS–RT data for the same trip.

Phone global positioning system (GPS) data from 12 trips between September 2022 and November 2022 were collected from the King County Metro (KCM) bus network. Phone data and GNSS receiver data were also collected from three trips on March 12, 2024. The phone data were collected using an Apple iPhone 11. The GNSS receiver data was collected using an Emlid Reach RS2. Realtime kinematic corrections for the GNSS receiver data were gathered through NTRIP from the Washington State Reference Network (WSRN). The masking angle of the GNSS receiver was set to a 20° elevation angle. Both the phone and GNSS receiver were mounted to a cradle and carried level at the center of the bus at approximately window-height. Typical phone sensor GPS precision is 16 ft (*40*). Typical dual-frequency receiver precision can be sub-centimeter under ideal conditions.

Estimating Block Energy Consumption with GTFS and GTFS–RT

A basic GTFS feed describes a set of stop times and locations for all scheduled trips in the bus network. A “trip" denotes a single run of a given route. Each trip is carried out by a single vehicle. A “block" denotes a series of trips which are scheduled to be carried out consecutively on a given service day by a single vehicle. To estimate daily bus network energy consumption, the energy consumed on all blocks is combined according to Equation 1.

$$Daily\ Network\ Energy = \sum_{i=1}^{n} \left[\left(\sum_{j=1}^{m} \hat{C_{ij}} d_{ij} + TQp_{ij} + Pl_{ij} + C_l s_{ij} \right) + C_l (U_i + V_i) \right] \tag{1}$$

$$Q = (t_i - T_o) av \rho c \cdot \frac{3{,}600\ s}{1\ hr} \cdot \frac{1\ kW}{3412\ BTU/hr} \tag{2}$$

where:

- n is the number of blocks scheduled on the service date.
- m is the number of trips in block i.
- $\hat{C_{ij}}$ is the estimated drive cycle energy consumption (kWh/mi) of trip j in block i.
- d_{ij} is the total distance (mi) of trip j in block i.
- T is the assumed door open/close time (hr).
- Q is the assumed door heat energy flux (kW) from Equation 2 limited to the volume of air in the cabin.
- p_{ij} is the number of stops on trip j in block i.
- P is the assumed auxiliary power (kW) used during trip layovers.
- l_{ij} is the layover time (hr) between the end of trip j and the start of trip $j+1$ in block i.
- C_l is the assumed deadhead energy consumption (kWh/mi).
- s_{ij} is the layover Manhattan distance (mi) between the end of trip j and the start of trip $j+1$ in block i.

- U_i is the Manhattan distance (mi) between the depot and the start of block i.
- V_i is the Manhattan distance (mi) between the depot and the end of block i.

and:

- t_i is the temperature inside the bus cabin ($65°F$).
- T_o is the assumed temperature outside the bus ($°F$).
- a is the area of the bus door ($32\ ft^2$).
- v is the wind speed through the door ($0.5\ ft/s$).
- ρ is the density of air at sea level ($0.0765\ lb/ft^3$).
- c is the specific heat of air at sea level ($0.241\ BTU/lb\text{-}°F$).

Trip and layover distances and times can easily be calculated from scheduled stop locations and times in a GTFS feed. Depot locations are approximated using k-means clustering of all block start locations. This approximately minimizes the total block deadhead distance driven to the start of all blocks. The baseline number of depots is based on the density of depots in the KCM network. The KCM network contains seven depots covering 2,135 square miles, or .003 depots per square mile (*41, 42*). A minimum of one depot is imposed for all networks. Since the driver may occupy the vehicle during layovers, the auxiliary power used between trips is assumed to be the same as during trips (Appendix 10). The baseline energy consumption used to travel between trips is assumed to be the FASTSim-estimated Manhattan drive cycle energy consumption for the design vehicle (2.77 kWh/mi).

The remaining challenge and focus of this study is to estimate $\hat{C}$ (i.e., the in-service vehicle energy consumption in kWh/mi) on a trip-by-trip basis for any bus network. First, an aggregation methodology proposed in prior work is tested on each route in the KCM network (*29*). This method breaks each route into 100 m uniform-distance segments then aggregates observed speeds collected from a GTFS–RT feed to their nearest segment. The speed profile is determined by the mean speed of the observations assigned to each segment. Since the “shapes.txt" field is optional and not available in the GTFS feeds of all transit networks, the route shape was determined by the stop locations.

Building drive cycles by aggregating prior observations to road segments requires pre-collected GTFS–RT or AVL data to provide speeds for the routes and times of interest. Using this same pre-collected data, travel time models can be developed and used to predict speed profiles on new routes. This allows the analysis to be extended to new bus networks without GTFS–RT feeds, or without archived data to aggregate. This study applies the generalizable travel time models built in (*13*) to this task. Note that the irreducible error in the travel time models was found to range from 9-15%. An additional error of 3-10% was incurred when generalizing to bus networks not in the original training set.

Data from the 33 international bus networks used in this study were collected from public GTFS and GTFS–RT feeds during the month of April 2024. Trip, route and stop information used in modeling were drawn from the service IDs corresponding to the first Wednesday of the month for each network.

The travel time models were applied to the same 100 m uniform-distance trip segments as used in the aggregation method. However, rather than aggregate GTFS–RT observations, the

models were used to impute segment-by-segment travel times for each trip in the target network's GTFS feed. Using the static distances (100 m) and the imputed travel times, a drive cycle of speed over time was synthesized for every trip. The time of day embedding for each trip (an input to the travel time models) was based on the initial stop time reported in the GTFS feed. This makes the estimated drive cycles sensitive to varying traffic conditions. For both drive cycle construction methods, a Savitzky-Golay filter was applied to smooth the velocity profile (*29, 35, 43*). FASTSim was then used to calculate the estimated energy consumption ($\hat{C}$) for each drive cycle.

Sensitivity Analysis

The energy consumption for all blocks in each of 33 international bus networks was estimated using the predicted drive cycle method. A sensitivity analysis is performed on the assumed parameters in Equations 1 and 2 (T, P, C_l, U_i, V_i, T_o) to determine the impact of various operational treatments on BEB viability across these networks (Table 2).

TABLE 2 Sensitivity Parameters Affecting Block Energy Consumption

Treatment	Baseline	Tested Range	Parameters Affected
Acc./Dec. Aggressiveness	1.00	[0.1, 5.0]	$\hat{C_{ij}}$
Passenger Load	41 *persons*	[1, 82] *persons*	$\hat{C_{ij}}$
Auxiliary Power	20 kW	[0, 40] kW	$\hat{C_{ij}}$, P
Deadhead Consumption	2.77 kWh/mi	[2, 5] kWh/mi	C_l
Depot Density	.003 mi^{-2}	[.001, .006] mi^{-2}	U_i, V_i
Door Open Time	30 s	[10, 120] s	T
Outside Temperature	46 $°F$	[20, 90] $°F$	T_o
Depot Plug Power	50 kW	[50, 350] kW	-

The sensitivity analysis is performed by varying each parameter in Table 2 over the range specified. The energy consumption for all blocks in each network is then re-estimated using the new parameter values. The results are then aggregated across all networks to determine the impact of each parameter on energy consumption, and the viability of BEB technology across all networks.

The acceleration/deceleration aggressiveness parameter is modeled by applying a weighted moving average filter to the drive cycle which boosts or decreases the amplitude of the drive cycle speeds. For each window, the difference of the signal from the window-mean (S_{y_i}) is boosted by an acceleration/deceleration aggressiveness scalar B (Equation 3).

$$\hat{y_i} = B(y_i - \frac{1}{2w}\sum_{i-w}^{i+w} y_i) \tag{3}$$

Power consumption by the HVAC system due to door open time and outside temperature parameters was modeled based on simple assumptions regarding airflow in/out of the cabin and heat capacity of that air at sea level (*44*) (Equation 2). This simplification limits the findings by not modeling interior temperature (which would include conductive and convective losses). Thus, under extreme conditions, this model does not guarantee a comfortable cabin temperature. It does however use the auxiliary sensitivity parameter to account for the full range of HVAC power that the design vehicle can output using the auxiliary sensitivity parameter.

Charging needs are modeled using a simple, unmanaged depot-charging approach. At the end of each block, the bus is assumed to return to the depot and charge at full available plug power until the total consumed block energy is recharged. This approach does not account for possible opportunity charging at stops or along the blocks. It does not account for the possibility of charging at a rate less than the plug power to minimize peak loads, or during off-peak hours. It also does not account for possibly limited plug capacity at the depots, or swapping low- and high-SOC vehicles to other blocks between service days. It is intended only as a rough preliminary estimate of fleet charging needs, to inform more advanced and potentially cost-saving strategies such as on-route or managed charging.

RESULTS AND DISCUSSION

Energy Modeling with Open and Standardized Bus Data

Validation of GTFS-RT Energy Estimates with Phone and GNSS Receiver Data

To understand the accuracy of energy predictions built on low resolution GTFS–RT, data were collected from a phone and GNSS receiver for three trips. These high resolution sources were used to directly construct three validation drive cycles. Figure 1 shows the speed profiles of the phone and GNSS receiver location data. The speed profiles are calculated based on the time derivative of position reported from each data source. The three high resolution drive cycles created for these trips were compared to drive cycles derived from the GTFS–RT data for the exact same vehicles.

Without filtering, the phone and GNSS trajectories have rare but large GPS point errors giving spikes of acceleration and deceleration. The phone and GNSS sources are very similar, while the GTFS–RT differs due to its low sampling frequency. Applying a Savitsky-Golay filter to the phone, GNSS and GTFS–RT speed profiles reduces the RMSE between the phone and the GNSS from 5.0 mph to 2.6 mph, and between the phone and the GTFS–RT from 10.5 mph to 9.1 mph. Despite the relatively small improvement in signal RMSE between the phone and GTFS–RT speeds (-13%), the RMSE in energy consumption between them improves significantly from 0.29 kWh/mi to 0.07 kWh/mi (-76%). For comparison, the RMSE in energy consumption between the smoothed phone and GNSS cycles is 0.03 kWh/mi. Given that standard drive cycles give consumption in the realm of 1.98–2.77 kWh/mi (as shown in Table 1), this is a relatively small error.

The agreement in cycle consumption is driven by several factors. First, there is a large contribution of auxiliary power to each cycle's overall energy consumption. Auxiliary power is a fixed parameter of the design vehicle, and it has the same effect per unit time for each cycle. Due to the dominant role of auxiliary power in the overall energy consumption, the impact of the cycle resolution differences is lessened. However, for higher speed trips, where drag and rolling resistance begin to dominate the energy consumption, the high-speed events missed in the GTFS–RT data will begin to have a larger impact on the overall consumption.

There are also many acceleration and deceleration events missed in the GTFS–RT cycles due to their lower temporal resolution. However, due to high maximum regenerative braking recovery for BEVs in FastSIM (98%) these are less impactful on overall consumption than they might be in a real-world scenario (these parameters were validated with Altoona testing in Table 1). More energy is typically spent accelerating than can be recovered decelerating with regenerative braking. This drives greater energy losses in the phone and GNSS cycles where there are more captured instances of acceleration and deceleration. For reference, reducing the maximum regenerative braking energy recovery to 0% increases the phone and GTFS–RT average consumptions



FIGURE 1 Clipping speeds to physical limits and applying a Savitzky-Golay filter to the phone, GNSS and GTFS–RT data reduces the root mean squared error
(root mean squared error (RMSE)) between the phone and GNSS by 2.3 mph, and between the phone and the GTFS–RT by 1.4 mph.

by 1.07 kWh/mi (64%) and 0.85 kWh/mi (52%) respectively.

Last, the ascent energy data reveal a challenge with using GTFS–RT data for elevation analysis. Using the shortest path between consecutive GPS points when interpolating the trajectory and sampling the DEM leads to "corner cutting" for the lower resolution trajectory. As shown in Figure 2, this can create spikes in elevation (e.g., when the shortest distance between GPS points traverses a hill that the actual roadway goes around).

In theory, the elevation data used as input to FASTSim should be identical for both cycles. This means that the power consumed in gaining elevation or regained from regenerative braking should be nearly the same for both sources. However, the elevation spike from the low resolution creates discrepancies in the power required to drive the cycle which contributes to error in net consumption.

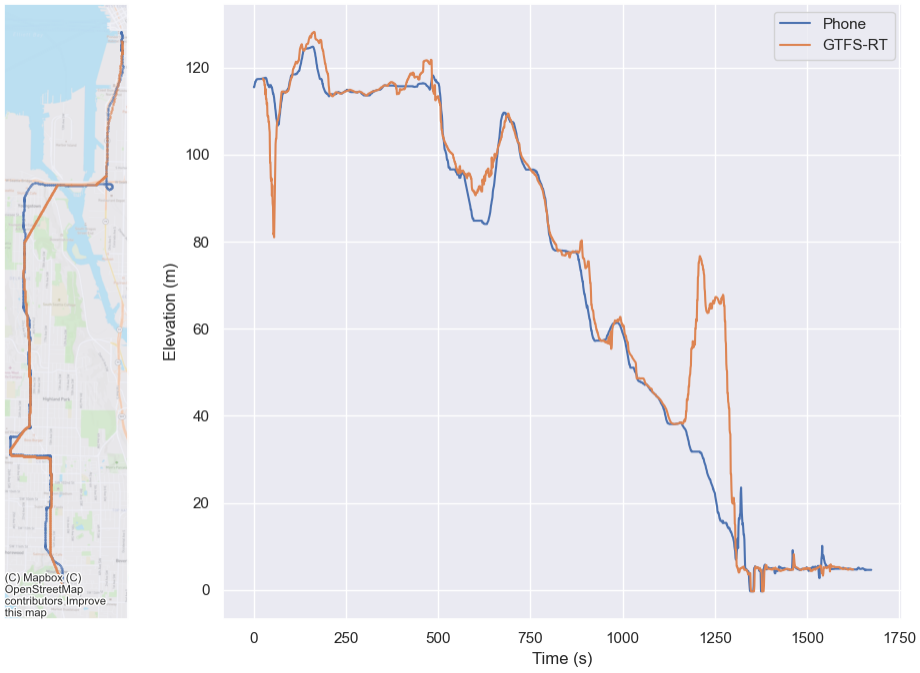


FIGURE 2 One of the validation trips and its elevation profile for phone and GTFS–RT data sources. In the second half of the trip (as the vehicle approaches sea-level) the low resolution GTFS–RT data create an error in the elevation profile.

Implications on Using the GTFS–RT Standard for Energy Modeling

The results demonstrate that drive cycles built on GTFS–RT tend to slightly underestimate energy consumption. This is driven by missed acceleration events that create higher aerodynamic and rolling resistance forces. The validation trajectories built on phone/GNSS receiver sources found a difference in estimated consumption of 0.29 kWh/mi compared to the GTFS–RT data. This was reduced to 0.07 kWh/mi by applying a Savitsky-Golay filter to both sources.

In this case, the relatively low error was accomplished due to the regenerative braking recovery, auxiliary power and (usually) identical elevation profiles of each source. At times, the low resolution of the GTFS–RT data led to differing elevation profiles. High contribution of auxiliary loads to trip energy consumption reduced the relative impact of drive cycle inaccuracies, especially for slow trips. If the same methodology were applied to non-BEB drive cycles, the lack of regenerative braking recovery would lead to greater power required for acceleration, and a larger discrepancy in consumption estimates. With a high resolution GTFS–RT feed, the discrepancy in consumption estimates would be reduced.

The GTFS–RT standard also uses low resolution ridership data (e.g., low, medium or high crowding) (*45*). In the next section, differences in weight due to passenger load are shown to have an effect on energy consumption and block electrification viability. With more precise ridership data, the energy consumption of each block could be more accurately estimated. Higher resolution ridership data may also enable better estimates of door open/close times and auxiliary loads, which are also shown to have a significant impact on energy consumption. Last, the optional block ID parameter in the GTFS standard limits the trip-by-trip analysis for some networks.

Cross-Sectional Sensitivity Analysis

Modeling Baseline Blocking Constraints with KCM Network

Network-wide predicted bus drive cycles were used to model total energy needs for any given transit network. The energy consumption of each block ($\hat{C_{ij}}$) was first estimated using the predicted drive cycles and FASTSim, then applied to Equation 1. The total energy and distance of each block including deadhead give a mean block consumption of 3.14 kWh/mi.

Total block energy requirements impose constraints on the blocks which can be electrified without opportunity charging. The battery capacity of the design vehicle (466 kWh) was used to determine the number of blocks that could be feasibly completed on a single charge. Under baseline assumptions, this was around 80% of blocks in the KCM network. The remaining 20% of blocks would require additional charging on-route, or larger BEB ranges. This is with new batteries; over the service life of the design vehicle (12 years) the number of blocks capable of being served would decrease as the battery capacity degrades. This might be addressed by rolling fleet replacements placing newer BEBs on the most energy-consuming blocks, as roughly 40% of blocks could still be covered by older vehicles with as little as half the usable battery capacity of a new BEB.

Under simple charging strategy assumptions the approximate power needs of the KCM network were also estimated. Figure 3 shows the number of active vehicles scheduled in the KCM GTFS, and the power demand of all charging vehicles per 15-minute period of the day. All vehicles were assumed to be BEBs, to charge immediately at baseline plug power upon return to their assigned depots, and to charge until fully replenished.

Assumptions of unmanaged charging lead to high overnight peak power demand due to the large number of vehicles returning to depots after the PM peak. The peak power demand is about 31.6 MW, and occurs near midnight. As higher plug power is assumed, the peak would become higher and coincide more and more closely with PM peak vehicles arriving at the depot (a generally more expensive time of day). This is in direct tension with daily pullout needs of the fleet: With unmanaged charging and a 50 kW plug power, only about 75% of scheduled vehicles would be recharged by their pullout time.

In order to electrify 95% of the fleet with unmanaged charging and meet daily pullout needs, a minimum plug power of 470 kW would be needed. This is on the upper range of available charger capacities, and many existing depots may not have the infrastructure to support this level of charging. This high upper tail is driven by long-duration blocks with relatively short scheduled down-times at the depot before departing.

Another way of framing charging needs is to divide the total network energy among the number of vehicle-hours available for charging at the depot. This more closely approximates the average power demand of the fleet under a scenario where managed charging is available. For KCM this is 21 kW per vehicle charging at the depot. In this case, the power curve would track the count of inactive vehicles in Figure 3. The peak power would occur when the most vehicles are at the base (i.e., still midnight) and would be 23.7 MW. This significant reduction in peak power demand would require a more complex charging strategy, but would also reduce the overall cost of electrification by through lower peak power demand costs.

The implication of these findings is that from an operational standpoint, many blocks can be quickly and easily electrified with no managed charging, no vehicle block swapping and no on-route charging. As a BEB fleet grows, the peak charging power required to meet all block pullouts would increase rapidly, at which point managed charging strategies could be deployed to reduce

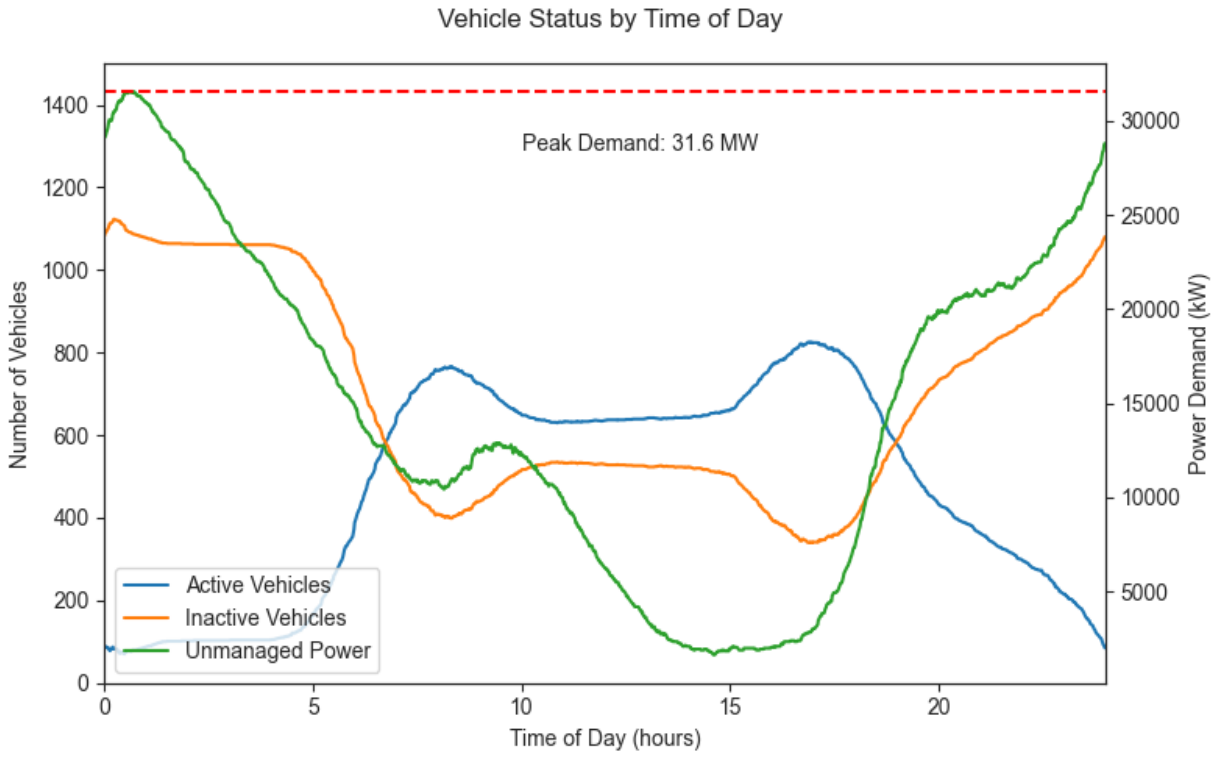


FIGURE 3 Active vehicles in the KCM network peak near 10AM and 5PM, with a large number of vehicles returning to depots after the PM peak. Higher baseline charging power increases the peak demand and shifts it to match vehicle arrival times.

peak power demand. The tradeoff between the costs of administering a managed charging strategy and the costs of peak power demand is a key consideration for transit agencies looking to electrify their fleets.

A sensitivity analysis was performed to determine the impact of operational parameters on block energy consumption and charging needs. The results for block energy are shown in Figure 4.

Auxiliary power has a strong effect on the energy consumption of BEBs in the fleet. Depending on the level of utilization it can lead to a difference of up to 3.0 kWh/mi. This level of uncertainty is highly undesirable for fleet electrification, as it can increase the energy required to run a block by up to 50% (Figure 4). If underestimated, this could lead to stranded BEBs or missed pullouts due to insufficient range or charging capacity.

Despite high uncertainty, Figure 4 shows that even under the worst-case scenario for auxiliary loads 10% of blocks could be electrified with a usable battery capacity of only 120 kWh. This is well within the capabilities of the BEB market today. However, to meet a full (95%) electrification scenario, many of the tested parameters would push blocks outside of that capable range.

Cross-Sectional Sensitivity Analysis for International Networks

For a more complete picture of agency needs regarding fleet electrification, the energy modeling and sensitivity frameworks were extended to GTFS and GTFS–RT feeds from 33 international bus

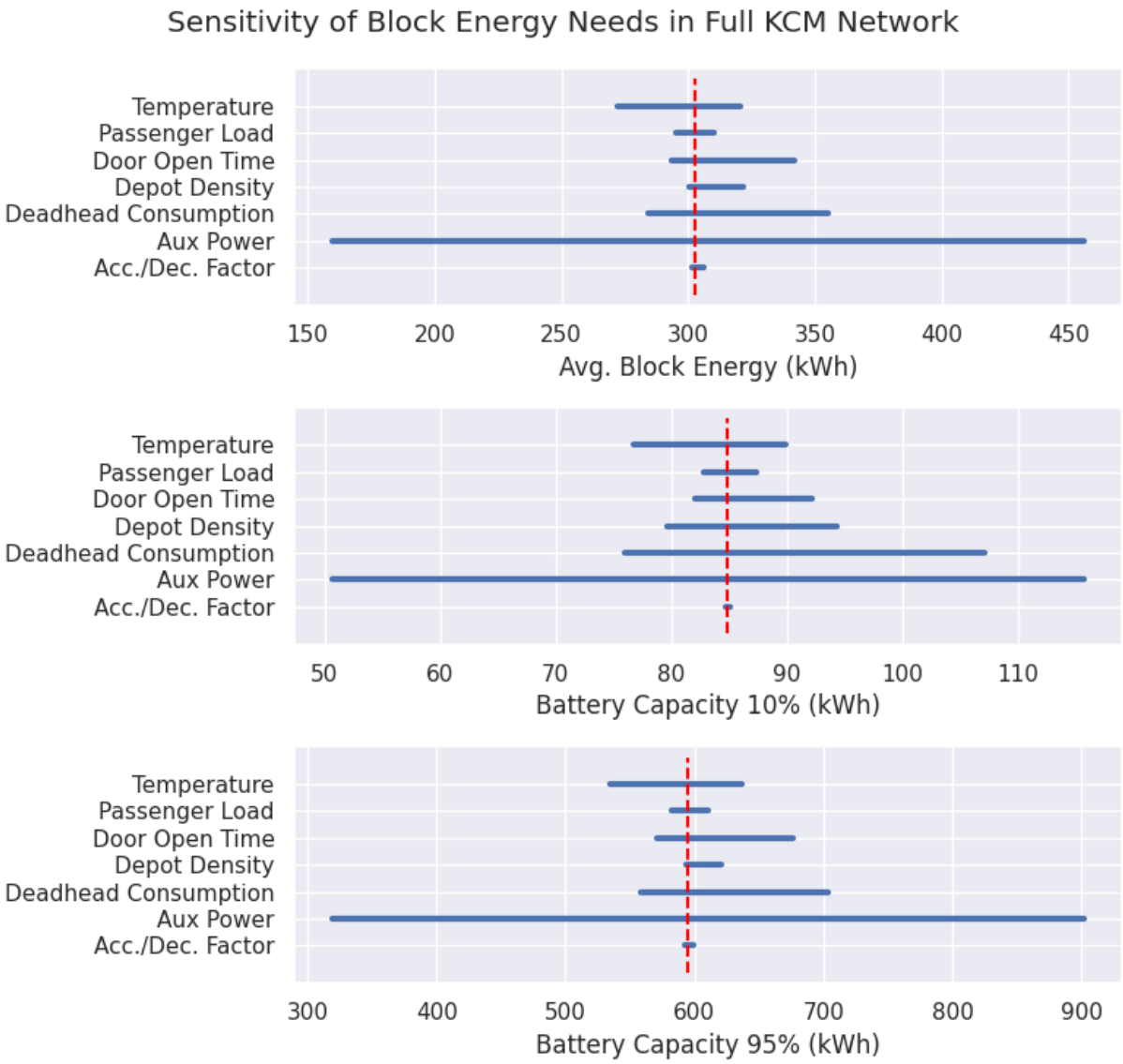


FIGURE 4 Sensitivity of required battery capacity to key operational assumptions, for average, 10th percentile, and 95th percentile routes in KCM network. Even under worst case auxiliary loads, 10% of blocks could be electrified with existing BEB technology. Current capacities are not sufficient for full fleet electrification.

networks (Appendix 11). For each network, key technological requirements for fleet electrification were determined. These included the minimum battery capacity needed to meet 10th and 95th percentile block energy needs, and the minimum plug powers needed to meet similar block pullouts. These results examine how the constraints to fleet electrification vary across different networks, and how aspects of the network can affect these constraints.

First, nearly every agency in the study could electrify 10% of their blocks with unmanaged depot charging. Figure 5 shows the battery capacity required to do so. The ranges shown represent the range of auxiliary loads considered in the sensitivity analysis, i.e. $0-40\ kW$. Note that the

GTFS standard lists “block_id" as an optional parameter. Only agencies reporting block IDs were considered in this study.

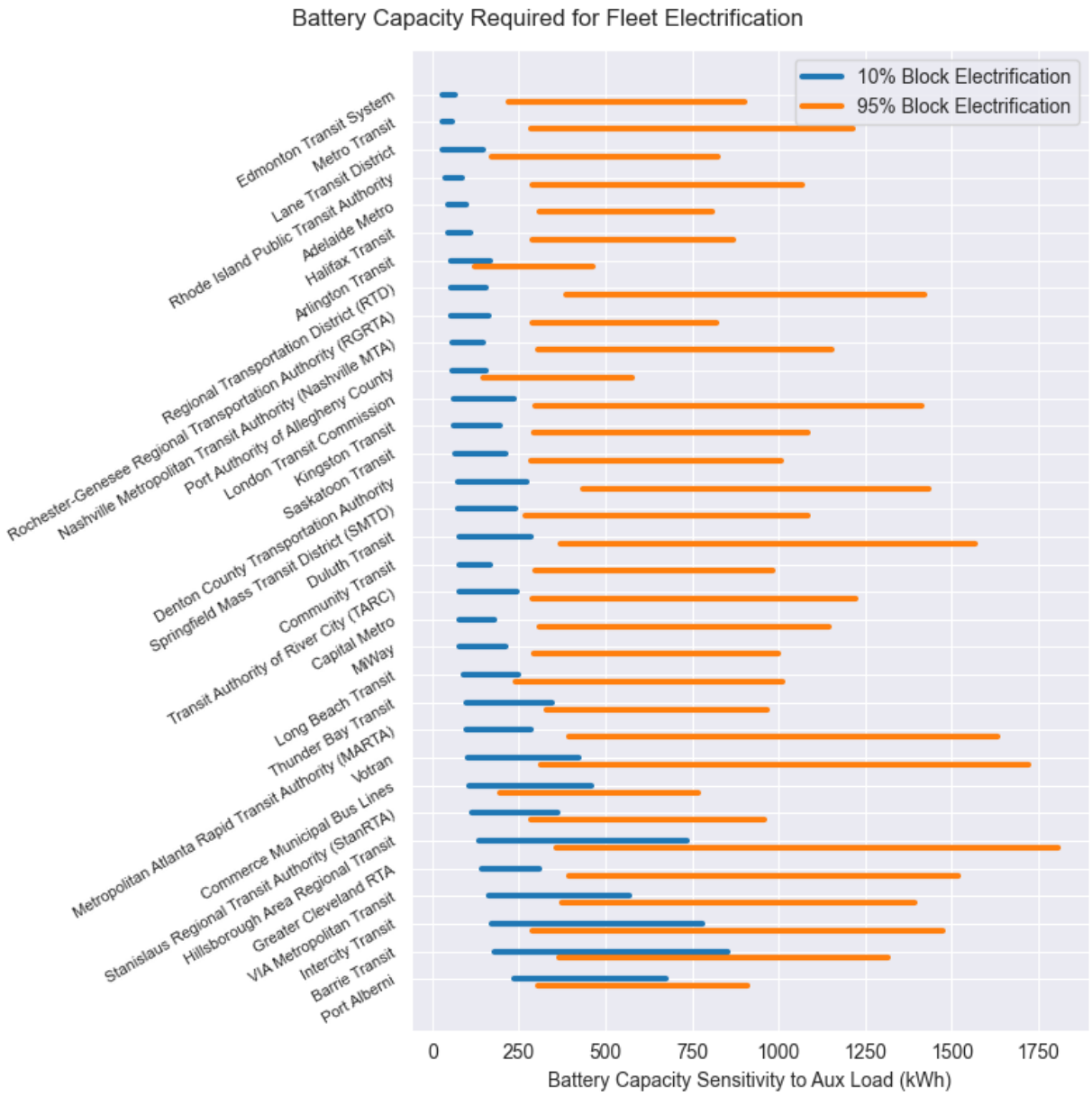


FIGURE 5 BEB battery capacities needed to electrify 10th percentile and 95th percentile blocks for 33 international agencies, under low and high auxiliary load assumptions. Nearly all agencies could electrify 10% of blocks with unmanaged depot charging, even under worst case auxiliary loads. Note that agencies not reporting block IDs are assigned one block per trip.

To achieve full BEB fleet electrification with the design vehicle for this study (466 kWh battery capacity), every agency listing block IDs would need to operate at the lowest end of auxiliary power. This assumes baseline values for other parameters such as temperature, driver acceleration

behavior and passenger load. Variation in these other conditions could further reduce the number of blocks that could be served by the design vehicle. Based on these findings, the current BEB market is inadequate for full fleet electrification. Many agencies are challenged with 2030 zero-emission goals which based on these results may be impossible without re-routes or other large operational changes.

Unmanaged charging is the simplest strategy from an implementation standpoint. It does not require equipment or personnel outside of chargers. For an initial fleet rollout, very low charger power can be used (results range from 10-100 kW to meet 10th percentile blocks). For full fleet electrification, the power required to meet block pullout becomes excessively high along with peak demand. There is no choice but to transition to managed charging.

The ideal charging management strategy charges vehicles as slowly as possible, while still meeting block energy pullout needs. To approximate the average power demand from a managed charging strategy, the total energy of the network is divided by the number of vehicle-hours available for charging at the depot. This assumes a lower-bound best case scenario for charging power where all vehicle pullouts can be met by swapping vehicles between blocks.

One strategy to reduce individual block energy needs and peak demands is to run more vehicles with shorter blocks. Figure 6 shows the relationship between the average block distance and average managed charging rate (per inactive vehicle) in the study networks. Speaking generally, longer blocks both 1) Consume more energy and 2) Take longer to complete. Under an unmanaged charging scenario, this means the agency must then consume more energy in a shorter period of time to re-charge the bus and still meet block pullout. These compounding factors create high plug powers at the depot.

Therefore, as shown in Figure 6, average and peak power can be greatly reduced by agencies running shorter blocks. This may be accomplished by splitting blocks and running more BEBs (or swapping BEBs between blocks). Given that BEBs typically have high capital and low operating costs, the extra vehicles may not justify the power savings.

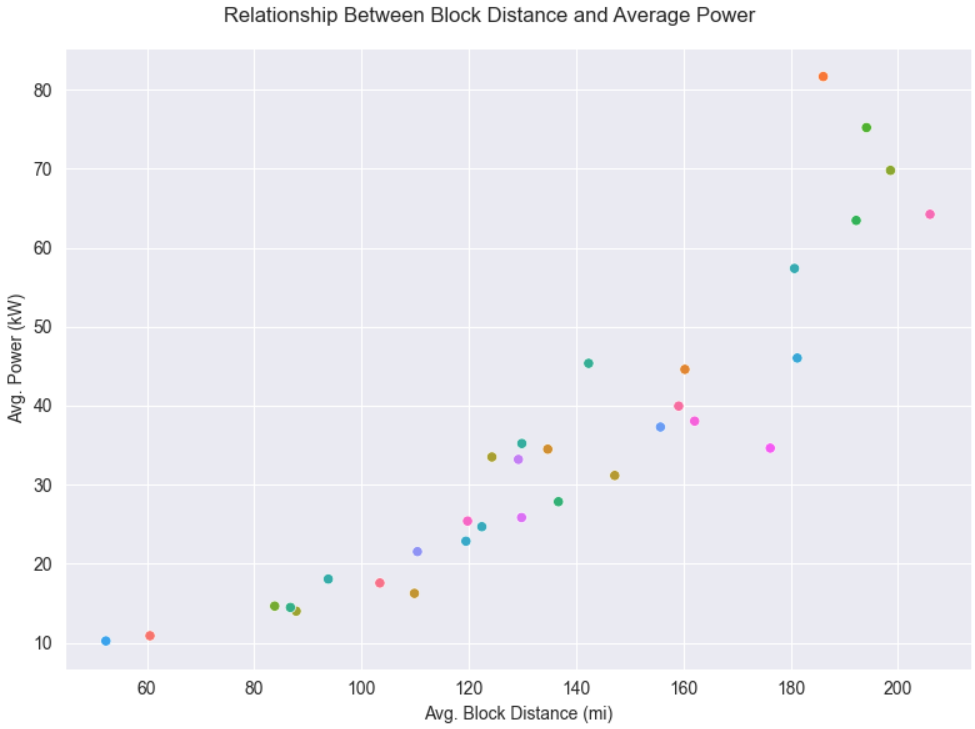


FIGURE 6 Decreasing block distance through block splitting or re-routing can greatly reduce average and peak power demands. Vehicles spend more time at the depot and can charge more slowly under a managed scenario. This comes at a tradeoff to operating more vehicles and having greater deadhead miles. Note that agencies not reporting block IDs are assigned one block per trip.

Implications on Viability of Fleet Electrification

Across the 33 international transit agencies in this study, most could support 10% block electrification with little to no managed charging — even under highly conservative estimates about auxiliary power loads. This makes BEB pilot projects relatively straightforward, though not necessarily cost effective. To evaluate the costs for a full fleet transition the capital and operational costs of the pilot BEBs would have to be weighed against potential federal funding, future BEB technology, and the specific needs of the network.

To support full electrification, BEB capacities of at least 500–1000 kWh are needed. This can be reduced through operational approaches such as driver acceleration and limiting door open time. However, by far the greatest source of uncertainty remains the auxiliary load. As a greater proportion of the fleet is electrified, peak demand and charger power to meet block pullouts will necessitate managed charging. Under best-case scenarios for managed charging, an average plug power as low as 30 kW per bus may be possible.

To meet net-zero goals with BEBs, vehicle battery capacities will need to improve significantly. Current charger powers may be sufficient to meet full-electrification goals with adequate plugs and managed charging strategies. Purchasing additional BEBs to run the same quantity of service miles would greatly reduce average block distance and thus average and peak charging power. Running these shorter blocks with lower capacity buses could also decrease consumption and total energy needs by using lighter vehicles with smaller batteries.

CONCLUSIONS

This work proposed a new method for developing BEB drive cycles specific to any transit network and demonstrated that method on a fleet electrification study of 33 international bus networks. A BEB design vehicle was first validated against Altoona testing data for standard cycles using FASTSim. The core data for the analysis came from GTFS and GTFS–RT which are standardized formats that can be readily collected for many transit networks. The study evaluated the shortcomings of the GTFS–RT data format for constructing drive cycles and the implications of using the standard for energy analysis. It also evaluated the sensitivity of network energy consumption and charging needs related to key operational parameters. Drive cycle findings were validated against individually-collected phone and GNSS receiver recordings onboard KCM buses.

The results show that the GTFS–RT standard is a useful tool for constructing drive cycles, but that the low resolution of the data can lead to underestimation of energy consumption by 0.03 to 0.25 kWh/mi (depending on the amount of post-processing for the validation and GTFS–RT data). This was especially true for cycles with sporadic acceleration events characteristic of urban bus routes. GTFS–RT drive cycles were found to underestimate high speeds leading to discrepancies in power due to aerodynamic forces. Auxiliary power and elevation changes were generally quite similar between data sources, as they were less affected by the low sampling frequency. Routes where low speeds and large elevation changes control BEB power thus lead to estimates on the more accurate side of the 0.03 to 0.25 kWh/mi range.

Results from a cross-sectional analysis of 33 international transit agencies revealed that with current technology, most agencies can readily electrify 10% of their blocks. This assumes completely unmanaged depot charging, the simplest operational strategy for BEB charging. As the proportion of blocks to be electrified grows, usable battery capacity becomes the main limiting factor. Capacities of 500-1000 kWh for the given design vehicle — or even more under worst-case auxiliary load assumptions — would be needed to electrify all blocks; these are on the upper limit

of the market today. To meet block pullouts under increasing electrification, managed charging is essential. Under perfect efficiency, most agencies incur an average power demand of 30 kW per-vehicle at the depot. The compounded relationship between average power demand and average block distance means that more vehicles serving the same number of service miles may be a viable way to reduce peak and average power demand.

Limitations of this study include assumptions regarding depot locations, deadhead distances and charging strategies. In future work, more precise locations and routing decisions for deadhead trips could be modeled to improve energy consumption estimates. Managed charging strategies, including on-route opportunity charging could greatly reduce the BEB capacity needed to meet block pullout needs. They may also reduce peak power demands and required depot charging power.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Z. Aemmer, D. MacKenzie; data collection: Z. Aemmer, D. MacKenzie; analysis and interpretation of results: Z. Aemmer, D. MacKenzie; draft manuscript preparation: Z. Aemmer, D. MacKenzie. All authors reviewed the results and approved the final version of the manuscript.

DECLARATION OF CONFLICTING INTERESTS

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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APPENDIX A: BEB VEHICLE PARAMETERS BASED ON 2022 NEW FLYER XE40

Vehicle Parameter	Value	Source
Drag Coefficient	0.60	FASTSim Class 8 Truck
Frontal Area	10.78 m^2	Altoona Testing Report
Center of Gravity	0.53 m	FASTSim Class 8 Truck
Drive Axle Weight	64 %	Altoona Testing Report
Wheelbase	7.2 m	Altoona Testing Report
Weight	18,230 kg	Altoona Testing Report
MC Max Power	230 kW	Altoona Testing Report
MC Time to Max Power	4 s	FASTSim BEVs
ESS Max Power	1,000 kW	FASTSim BEVs
ESS Max Energy	466 kWh	Altoona Testing Report
ESS Round Trip Efficiency	0.97	FASTSim BEVs
Wheel Inertia	0.82 kg/m^2	FASTSim Class 8 Truck
Number of Wheels	6	Altoona Testing Report
Wheel Rolling Resistance Coefficient	0.006	FASTSim Class 8 Truck
Wheel Radius	0.51 m	FASTSim Class 8 Truck
Wheel Coefficient of Friction	0.70	FASTSim Class 8 Truck
Min State of Charge	10 %	FASTSim BEVs
Max State of Charge	95 %	FASTSim BEVs
Alternator Efficiency	100 %	FASTSim BEVs
Auxiliary Power	10.2 kW	Altoona Testing Report
Transmission Efficiency	98 %	FASTSim BEVs
Max Braking Regeneration	98 %	FASTSim BEVs
Time 0-60 MPH	60 s	Altoona Testing Report

APPENDIX B: INTERNATIONAL TRANSIT NETWORKS WITH OPEN BUS FEEDS

Provider	Min Lon	Max Lon	Min Lat	Max Lat	Timezone	EPSG
London Transit Commission	-81.36311	-81.137591	42.905244	43.051188	America/Toronto	32617
Barrie Transit	-79.74063237	-79.61089569	44.3218044	44.42020676	America/Toronto	32617
Capital Metro	-97.9911	-97.370389	30.147252	30.587897	America/Chicago	32614
Regional Transportation District (RTD)	-105.584149	-104.669533	39.456877	40.206556	America/Denver	32613
Intercity Transit	-122.977127	-122.483109	46.93304	47.16091	America/Los_Angeles	32610
Duluth Transit	-92.290788	-92.009608	46.654703	46.855417	America/Chicago	32615
Votran	-81.506774	-80.847351	28.856002	29.383995	America/New_York	32617
Nashville Metropolitan Transit Authority (Nashville MTA)	-87.379122	-86.29724	35.7416	36.525005	America/Chicago	32616
Transit Authority of River City (TARC)	-85.904275	-85.502994	38.056361	38.383253	America/Kentucky/Louisville	32616
Metropolitan Atlanta Rapid Transit Authority (MARTA)	-84.669803	-84.083398	33.432372	34.105822	America/New_York	32616
Springfield Mass Transit District (SMTD)	-89.75837	-89.527032	39.667827	39.898621	America/Chicago	32616
Metro Transit	-89.563863	-89.244818	42.987718	43.176537	America/Chicago	32616
Port Authority of Allegheny County	-80.258865	-79.70545	40.273078	40.667597	America/New_York	32617
Arlington Transit	-77.162277	-77.049105	38.839365	38.925147	America/New_York	32618
Rochester-Genesee Regional Transportation Authority (RGRTA)	-78.141093	-76.99341	42.526438	43.297343	America/New_York	32617
Adelaide Metro	138.445316	139.036087	-35.339223	-34.571043	Australia/Adelaide	32754
Edmonton Transit System	-113.934884	-113.218139	53.302688	53.704407	America/Edmonton	32612
Saskatoon Transit	-106.760746	-106.550137	52.078661	52.202189	America/Regina	32613
MiWay	-79.797795	-79.512874	43.469292	43.838069	America/Toronto	32617
Kingston Transit	-76.66738	-76.43906	44.2175	44.27897	America/Toronto	32618
Halifax Transit	-63.858243	-63.28321	44.565098	44.886253	America/Halifax	32620
Thunder Bay Transit	-89.38849	-89.1819	48.34626	48.47868	America/Toronto	32616
Port Alberni	-124.85047	-124.78265	49.21847	49.27743	America/Vancouver	32610
Commerce Municipal Bus Lines	-118.264252	-118.127642	33.965568	34.063075	America/Los_Angeles	32611
Stanislaus Regional Transit Authority (StanRTA)	-121.898961218	-120.74953	37.25713	37.954866	America/Los_Angeles	32610
Long Beach Transit	-118.447726	-118.063516	33.742939	34.069347	America/Los_Angeles	32611
Hillsborough Area Regional Transit	-82.584777	-82.210817	27.70568	28.195743	America/New_York	32617
Greater Cleveland RTA	-81.96736	-81.437811	41.227828	41.637051	America/New_York	32617
Lane Transit District	-123.3561683	-122.1152746	43.7849362	44.2226569	America/Los_Angeles	32610
Rhode Island Public Transit Authority	-71.829808	-71.154292	41.372687	42.016993	America/New_York	32619
Denton County Transportation Authority	-97.31863987	-96.926476	32.92199276	33.253687	America/Chicago	32614
VIA Metropolitan Transit	-98.711	-98.306921	29.27663	29.650497	America/Chicago	32614
Community Transit	-122.38471	-121.601001	47.59201	48.278539	America/Los_Angeles	32610

APPENDIX C: DATA SAMPLE AND CODE

Data sample and modeling code are available on Github at https://github.com/zackAemmer/open_bus_tools. We are happy to provide the full data set upon individual request.