Simulation of an Electric Transportation System at The Ohio State University

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Abstract

We use longitudinal dynamics and simulation models to study the feasibility of deploying electric buses in place of conventional ones. The longitudinal dynamics model estimates energy use by an electric bus operating on different lines consisting of a mixture of urban and suburban driving. The simulation model is used to study the effect of the type and number of chargers deployed and the queuing policy used on queuing and charging times when buses must recharge their batteries. We use a case study based on the bus service operated on The Ohio State University campus and focus on six of the seven lines which operate around the center of campus. We demonstrate that all 22 of the buses on these lines can be made electric and that one 500 kW or two 250 kW chargers are sufficient to maintain reasonable service frequencies.

Key words: Electric vehicle, bus, charging infrastructure, queuing model

1. Introduction

Concerns about gasoline prices, dependence on foreign energy sources, and environmental issues associated with using fossil fuels have increased interest in hybrid- and pure-electric vehicles. This includes a recent focus on heavy-duty vehicles, such as municipal buses. For instance, Wirasingha *et al.* [1] examine the economic viability and cost savings of the Chicago Transit Authority deploying plug-in hybrid electric buses in their fleet. Although electric buses have lower driving costs than conventional gasoline or diesel buses, they have considerably higher upfront capital costs. Informal conversations with two bus manufacturers—Proterra, Inc., which produces pure-electric buses, and Gillig LLC, which produces conventional and hybrid-electric diesel buses—reveal large price differences. Proterra markets its electric bus for about $900,000, as opposed to $400,000 and $600,000 for Gillig's conventional and hybrid buses, respectively. Much of this cost difference is due to the large capacity of the battery. Due to vehicle mass and the need for a long driving range, an electric bus may have a 55 kWh or larger battery. The feasibility of electric vehicle deployment depends largely on proper vehicle design [2].

Furthermore, an electric bus fleet requires a charging infrastructure [3]. Unlike a conventional bus, which can often complete a shift without refueling, an electric bus may need to recharge multiple times in a day. To maintain reasonable bus service frequencies, this charging must typically be done within a relatively short time frame. One option is to install chargers that the buses directly use. Proterra, for example, markets a 250 kW bus charger for about $250,000. This could charge a fully-depleted 55 kWh battery in about 15 minutes (assuming 90%-efficient charging). An alternative is to use battery-swapping stations, which keep an inventory of charged batteries that can be swapped into buses between trips. Because batteries in

the station are charged continuously (as opposed to only between trips, as with a dedicated bus charger), lower charging rates can be used. Battery swapping can be costly, however, since an inventory of additional batteries is needed. The battery is one of the most expensive components in an electric bus. Nevertheless, this model has been used, for instance by the electric bus fleet used to transport athletes to and from the Olympic Village at the 2008 Beijing games.

Thus, charging infrastructure design and layout is an important consideration in deploying an electric bus fleet. This is due to the tradeoff between minimizing infrastructure cost and maintaining reasonable service levels. Charging-infrastructure problems belong to the broader class of refueling-infrastructure problems, which is studied in a number of previous works. Langford and Cherry [4] examine the deployment of hydrogen buses by the transit authority in the Knoxville, Tennessee area. They use geographic information system data to find the best sites at which to install hydrogen refueling stations for use by the transit authority and individuals with hydrogen-powered vehicles. They assume staggered refueling before or after each bus enters or exits service. Other works examine the deployment of electric vehicle chargers, but focus on light-duty vehicles. Ip *et al.* [5] determine the location of charging stations using a hierarchical clustering method. Their approach is to convert road information into demand clusters and assign each cluster one charging station. Frade *et al.* [6] propose a maximal covering model, which determines the location of charging stations by maximizing the demand covered within an acceptable distance of the stations. The demands are determined based on the number of vehicles at each city block.

The aim of this paper is to expand upon these works and examine the use of an electric bus fleet for passenger service. We do this using a case study based on the Campus Area Bus Service (CABS) operated on The Ohio State University's main campus. Specifically, we develop an electric bus energy model, which determines the energy used by buses on the different lines operated by the CABS, based on the associated duty cycles. We also develop a simulation model to examine how electric bus charging patterns and queuing times are affected by the number of chargers deployed in the system and the charging policy employed. We demonstrate that a standard first-in/first-out policy results in the highest queuing times, implying that the CABS could not maintain its current bus schedule if such a policy is used. Rather, a highest attribute value policy, which prioritizes buses with the highest state of charge (SoC) first, achieves the shortest queuing times. Overall, we demonstrate that with proper investments, the CABS fleet can be electrified with minimal disruption to service levels. The remainder of this paper is organized as follows: Section 2 discusses our bus model and provides some validation results. Section 3 details the simulation model used to study charging patterns and the different charging policies examined. Section 4 details the CABS and our case study and assumptions. Section 5 summarizes our results and Section 6 concludes.

2. Bus Model

We model electric bus energy consumption using a backward approach [7, 8, 9]. This technique starts with a specific driving cycle, which is used to calculate vehicle longitudinal dynamics as a function of velocity. From these dynamics we compute torque and rotational speed at the wheels. Then, by accounting for transmission losses, we use motor maps to determine electric energy use.

We model the longitudinal dynamics of the bus as:

$$(M + M_{equ})\frac{d}{dt}V(t) = F_{MW}(t) - F_{total}(t), \tag{1}$$

where M is the vehicle mass, M_{equ} accounts for the rotational inertia of the vehicle components, $V(t)$ is the velocity, $F_{MW}(t)$ is the motor force at the wheels, and $F_{total}(t)$ is the vehicle road load. $F_{MW}(t)$ represents the force that the powertrain must supply to the wheels to overcome $F_{total}(t)$. We assume that:

$$M_{equ} = 0.1 \cdot M, \tag{2}$$

meaning that the rotational inertia of the vehicle components is approximated as being 10% of the linear inertia of the vehicle. The literature [10, 11, 12] suggests different ways to estimate this parameter, showing

2

that it could vary between 7% and 13%. For the purposes of our model, we believe 10% is a reasonable approximation of this range, since it allows us to evaluate overall vehicle energy expenditure.

We assume the vehicle road load is defined as the sum of the resistance forces acting on the vehicle, and is given by:

$$F_{total}(t) = F_a(t) + F_r(t) + F_g(t) + F_{acc}(t), \tag{3}$$

where $F_a(t)$ and $F_r(t)$ are the aerodynamic and rolling resistance forces, respectively, $F_g(t)$ is the grade force for non-horizontal roads, and $F_{acc}(t)$ is the accessory force. The aerodynamic resistance force is caused by the friction of the air that surrounds the vehicle surface and the pressure difference that exists between the front and back of the vehicle. Thus we compute it as:

$$F_a(t) = \frac{1}{2}\rho_a \cdot A_f \cdot C_d \cdot V_{eff}(t)^2, \tag{4}$$

where ρ_a is the air density, A_f is the frontal area of the vehicle, C_d is the drag coefficient, and $V_{eff}(t) = V(t) - V_{wind}(t)$ is the relative velocity between the vehicle and the air. At low velocities the rolling resistance force is the primary force opposing the motion of the vehicle. We assume it is given by:

$$F_r(t) = C_r(V(t)) \cdot M \cdot g \cdot \cos\alpha, \tag{5}$$

where g is standard gravity and α is angle of the road with the horizontal. $C_r(\cdot)$ represents the rolling resistance coefficient, which can be determined as a function of vehicle speed and tire pressure. The grade force is defined as the gravitational force that acts on the vehicle, and is given by:

$$F_g(t) = M \cdot g \cdot \sin\alpha. \tag{6}$$

The motor force at the wheels can be defined as the motive force at the wheels that the powertrain must supply to overcome the road load. Thus it can be defined as:

$$F_{MW}(t) = \frac{1}{R_W}T_W(t), \tag{7}$$

where R_W is the wheel radius and $T_W(t)$ is the motor torque at the wheels. We can further define the power at the wheels as:

$$P_W(t) = T_W(t) \cdot \omega_W(t) = \eta_\tau \cdot T_M(t) \cdot \omega_M(t), \tag{8}$$

where $T_M(t)$ is the motor torque, $\omega_W(t)$ and $\omega_M(t)$ are the rotational speeds at the wheels and motor, respectively, and η_τ is overall transmission efficiency. We assume a fixed ratio between the rotational speeds at the wheels and motor:

$$\frac{\omega_M(t)}{\omega_W(t)} = \lambda_f \cdot \lambda_\tau = \lambda, \tag{9}$$

where λ_f is the final transmission efficiency and λ_τ the gear ratio. Substituting (9) into (8) gives:

$$T_W(t) = \eta_\tau \cdot T_M(t)\frac{\omega_M(t)}{\omega_W(t)} = \eta_\tau \cdot \lambda \cdot T_M(t). \tag{10}$$

Combining (1), (7), and (10) allows us to compute the motor torque. We use a motor efficiency map, which is specific to the electric machine in the bus, to interpolate the associated rotational speed at the motor. We finally use an assumed motor efficiency to determine instantaneous energy use (or regeneration, when braking) at the battery. We also add the accessory load, $F_{acc}(t)$. These power terms are integrated over the entire driving cycle to determine total energy consumption.

We do not aim to model the storage system of the electric bus in detail. Rather, we analyze energy consumption given vehicle parameters and driving cycles. We assume the bus uses a nano-lithium-titanate battery, which has extremely fast charging and discharging rates without incurring damage [13]. We assume a battery with a 55 kWh storage capacity, which represents about 6.5% of the gross vehicle weight, and that the battery can operate between 20% and 95% SoC.

The model is implemented using the `MATLAB/Simulink` software platform. We validate the model against two driving tests conducted by Proterra at the Altoona Bus Testing and Research Center. Proterra [14] provides detailed vehicle characteristics of its FCBE 35 bus, which was tested, and we use these characteristics in our model. It also reports the tested fuel efficiency of the bus on the standard Central Business District (CBD) driving cycle. Proterra reports average energy consumption of 1.70 kWh/mile on the CBD driving cycle. Our simulations estimate 1.60 kWh/mile, meaning that our model estimates energy consumption that is within 6% of their reported test results. Figure 1 shows the results of our model applied to the Proterra bus on the CBD driving cycle. Specifically, it shows simulated bus displacement, velocity, and battery SoC. Proterra also conducted another, proprietary driving test. Although we cannot publicly disclose the details of this driving test, the bus had average and maximum velocities of 26 and 69 km/h, respectively. Our simulated energy usage, based on this driving cycle, is within 5% of the tested energy consumption.
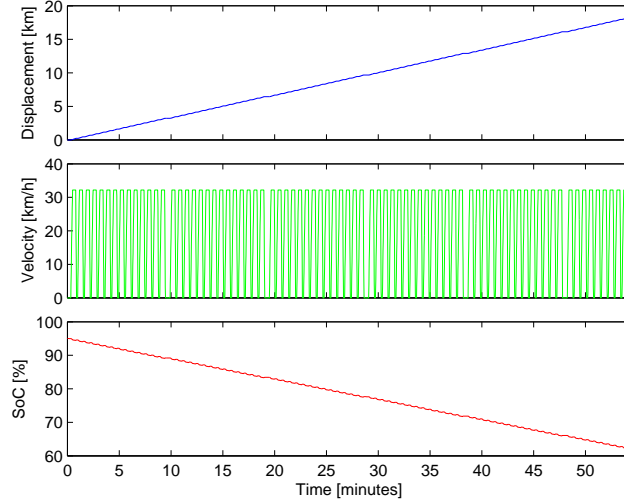

Figure 1: Simulated displacement, velocity, and SoC of Proterra bus on the CBD driving cycle.

While our modeling approach is widely used in the literature, it is a simplification of actual vehicle energy use. For instance, Trovão *et al.* [15] propose more sophisticated energy management strategies than what our model assumes. Since the focus of our analysis is on bus charging and queuing and queue management, this model provides relatively good inputs to our simulation model. Moreover, comparing modeled energy consumption to test data provided and reported by Proterra gives us confidence in these inputs.

3. Simulation Model

Our bus simulation model is divided into two parts—one that models bus trips along the lines in the system and another which models charging decisions by each bus and the resulting charging queues. Although we examine a mixed fleet, consisting of pure-electric and conventional buses, our model focuses exclusively on the former, since conventional buses do not use the chargers. The model first determines the time at which each bus enters the system. This entry time corresponds to when each bus begins it first trip during the period modeled. We assume that each bus begins this first trip with a fully-charged battery. Each bus route is divided into segments between each charging station along the line. We allow the travel time along each segment to be random, capturing variability of traffic and passenger loading and alighting patterns. We assume time-invariant travel-time distributions.

Figure 2 is a schematic diagram, summarizing the assumed logic when a bus arrives at a charging station. The model first updates the battery SoC, based on the SoC upon departing the previous charging station and the energy consumed in the segment just driven. Energy use is computed using the model detailed in Section 2. If a bus finds an unoccupied charger, it immediately occupies one and begins charging. Otherwise,

4

if all chargers are occupied but there is a charger without a queue, it randomly chooses an empty queue to enter. If a bus finds that all of the chargers are occupied and have non-empty queues, it determines if its SoC is sufficient to arrive at the next station along its route. If so, it exits the charging station and continues on its route. Otherwise, it enters the shortest queue available. Once a bus occupies a charger (either immediately upon arrival at a charging station or after queuing), it only charges sufficient energy to reach the next charging station. The queuing and charging logic assumptions are intended to minimize travel time disruptions to customers on the bus. Upon exiting the charging station, the battery SoC is updated to reflect any energy recharging, less inverter and other efficiency losses. The simulation continues in a loop in this fashion, as buses arrive and depart charging stations upon their routes. We implement this simulation model using `Arena` version 13.0, by Rockwell Automation.

4. Case Study: Campus Area Bus Service

The Ohio State University's main campus is located in Columbus, Ohio and is one of the largest in the United States with more than a 7 km^2 area, 457 buildings, and 55,000 students. The university also has five regional campuses throughout the state of Ohio in the cities of Lima, Mansfield, Marion, Newark, and Wooster. These regional campuses are excluded from this analysis. To ease on- and off-campus transport, the university operates the CABS. As shown in Figure 3, this consists of seven lines—North Express, Campus Loop North, Campus Loop South, Central Connector, East Residential, Buckeye Village, and Med Center Express. Buses run on these lines at different frequencies, depending on the time of day, day of week, and time of year. The peak operating period, during which buses run with the greatest frequency is 7:00 am to 7:00 pm on weekdays, during the autumn, winter, and spring quarters (when classes are in session).

CABS currently operates a mix of conventional and hybrid-electric diesel buses on these lines. Our case study assumes that these buses are replaced with all-electric models. Moreover, we exclude the Med Center Express line from this analysis, as it operates primarily outside of the center of campus. Whereas the other lines can share chargers due to overlap in their routes in the center of the campus, this would not be possible with the Med Center Express line.

Since actual velocity profile data for the six lines modeled are not available, we simulate these as a mixture of two bus velocity profiles that are standard in the literature [14, 16]. The Manhattan Bus Cycle (MBC) is intended to replicate an urban setting while the City Suburban Cycle (CSC) represents suburban driving. We use a mixture of these two due to the environment within and around the Ohio State University campus. Central campus can be compared to a small city, whereas the peripheral area is a mixture of residential and light-commercial buildings. Thus, each line is modeled assuming an MBC velocity profile in the center of campus and a CSC profile off campus. Figure 3 shows the boundary of the area that we consider to be central campus. To accurately estimate the mass of the bus in (1) we must account for passenger loads. Transportation and Parking (T&P) Services, which operates the CABS, periodically collects time-resolved passenger load data on its lines. Using a dataset for one of the lines, and by classifying the different stops on the lines as being in the 'urban' or 'suburban' zone, we generate passenger load profiles for the lines. We further assume each passenger and the bus driver to have a 70 kg mass, which is standard [14, 16]. Since the city of Columbus is nearly flat, we assume a 0% road grade on the entirety of each bus line. Table 1 provides summary data for the six lines modeled, including total length of each line, the percentage of those miles driven in the central campus area (corresponding to the MBC profile), the average per-cycle driving time, and the corresponding per-cycle energy use of the modeled electric bus. As expected, the table shows that the lines that spend more time in central campus have slower average velocities. These lines are also slightly less energy-efficient, since they require more kWh of energy per km driven. Figure 4 shows the simulated displacement, velocity, and SoC profile of a bus on the Campus Loop South line, starting from central campus. As expected, the portion of the route in central campus has frequent stops and a lower average and more variable velocity profile, due to planned stops and vehicle and pedestrian traffic. The bus is able to achieve higher velocities in the later part of the route, which is to the west of central campus. Similar velocity and energy use profiles are observed with the other lines.

Because it is the peak service period, during which all of the lines are operating with maximum frequency, our analysis focuses on the midday period from 7:00 am to 7:00 pm on weekdays. We assume that the buses

Table 1: Length, average driving time, and energy use of CABS lines modeled

Line	Length [km]	MBC [%]	Avg. Per-Cycle Time [min]	Avg. Per-Cycle Energy Use [kWh]	Efficiency [kWh/km]
North Express	6.28	38	23.2	8.41	1.34
Campus Loop North	8.66	34	30.5	10.91	1.26
Campus Loop South	8.66	34	31.2	11.08	1.28
Central Connector	9.17	52	32.4	12.11	1.32
East Residential	9.07	22	32.5	11.62	1.28
Buckeye Village	9.93	22	29.7	12.71	1.28

aim to maintain the same service frequency established by T&P—the North Express, Central Connector, and Buckeye Village lines run with five-, 12-, and 15-minute frequencies, respectively, while the remaining lines operate at 9-minute intervals. Based on the service frequencies and the mean cycle times listed in Table 1, T&P needs two, three, and five buses on the Buckeye Village, Central Connector, and North Express lines, respectively, and four buses on each of the remaining lines. We assume these numbers of electric buses are used on each line.

We assume that all chargers are placed at the same location, indicated on Figure 3, as all six bus lines modeled intersect at this point. This maximizes the use of each charger, and also minimizes ancillary costs, such as upgrades to distribution-level transformers. We model cases with up to four chargers, with either a 250 kW or 500 kW charging rate and 5% efficiency losses. Each bus is assumed to have a 55 kWh battery, the SoC of which can range between 20% and 95%. We assume that one bus begins service on each line at 7:00 am with a fully charged (*i.e.*, 95% SoC) battery. Subsequent buses begin service with fully-charged batteries at appropriate intervals after that. The time it takes each bus to complete a loop is assumed to have a triangular distribution, with the minimum, maximum, and mean travel time set based on historical travel time data provided by T&P. Energy usage during each trip is modeled as described in Section 2. However, we multiply this modeled energy use by a random scaling factor, which is uniformly distributed between 0.8 and 1.2 and randomly sampled for each trip. This scaling factor captures the inherent variability in energy use due to factors such as accessory force and passenger mass.

We consider three different bus queuing policies in our simulations: first in/first out (FIFO), lowest attribute value (LAV), and highest attribute value (HAV). The FIFO policy assumes that queued buses charge based on the order in which they join the queue. The other two policies prioritize charging based on the SoC of each battery. The LAV policy prioritizes buses with the lowest SoC, whereas the HAV policy charges buses with the highest SoC first. We simulate 1000 replications of each case (with different numbers of chargers and queuing policies) and use summary statistics to compare the effect of the different cases on queuing times and service levels.

5. Simulation Results

Tables 2 and 3 show average queuing and charging times for each bus in the course of a single loop along its designated line. As expected, they show that installing more chargers decreases queuing times, with a significant reduction when installing a second charger. They also show that installing more chargers tends to increase charging times. This is because with one or two 250 kW chargers, an average of about 16% and 8% of buses trips end with the bus skipping a charge, due to the charging queues being full. When a third charger is installed, virtually all buses recharge after each loop, as there are rarely full queues. Thus, the average time spent charging per trip increases when the third charger is installed. Similar results are observed with 500 kW chargers. The tables also show that a FIFO queuing policy performs the worst overall in terms of times whereas the HAV policy performs best. This is because the HAV policy prioritizes buses with the highest SoC, which also have the shortest charging times, first. Thus, the HAV policy results in faster turnover when there are buses in the queue.

In sum, it appears as though T&P would need to invest in at least one 500 kW or two 250 kW chargers to maintain a reasonable service level for an electrified CABS service. However, this depends on the extent

Table 2: Average per-bus cycle queuing and charging time with 250 kW chargers

Number of Chargers	Queuing Time [min]			Charging Time [min]		
	FIFO	LAV	HAV	FIFO	LAV	HAV
1	19.0	8.7	8.0	2.7	2.8	2.6
2	1.0	1.0	1.0	2.7	2.7	2.7
3	0.5	0.5	0.5	3.1	3.1	3.1
4	0.1	0.1	0.1	3.1	3.1	3.1

Table 3: Average per-bus cycle queuing and charging time with 500 kW chargers

Number of Chargers	Queuing Time [min]			Charging Time [min]		
	FIFO	LAV	HAV	FIFO	LAV	HAV
1	1.6	1.8	1.5	1.4	1.4	1.3
2	0.5	0.5	0.5	1.5	1.5	1.5
3	0.0	0.0	0.0	1.6	1.6	1.6
4	0.0	0.0	0.0	1.6	1.6	1.6

to which the service frequencies could be decreased. Two 250 kW chargers would result in an average of 3.7 minutes of additional time to each bus trip along a line, whereas one 500 kW adds at least 2.8 minutes. In addition to decreasing service frequency, electrification also results in passengers having to wait on the bus while it is queuing and charging. This additional delay and the associated inconvenience must be considered in a complete feasibility study.

6. Conclusions

Electric transportation offers many advantages over conventional technologies. This includes lower driving costs, higher energy efficiency, and the possibility of lower emissions [17, 18, 19, 20, 21, 22, 23, 24, 25]. There are, however, numerous challenges, including the higher upfront cost of electric vehicles and the need for charging infrastructure. A commercial vehicle fleet, such as a bus service, has the advantage that driving patterns are well known *a priori*, making it easier to site charging stations. The downside to an electric bus fleet, however, is that it can add queuing and charging times to each trip, decreasing service frequencies and increasing passenger wait times.

Using a longitudinal dynamics model we are able to estimate the energy use of an electric bus operating on different lines consisting of a mixture of urban and suburban driving. We combine this with a simulation model to study the effect of the type and number of chargers deployed and the queuing policy on service times. Using a case study based on the CABS at The Ohio State University, we estimate bus queuing and charging times. Importantly, we show that 22 buses can share one or two chargers, with minimal disruptions to the service frequencies. Should such service frequencies not be acceptable, other strategies could be employed. This includes adding more buses to each line, chargers with higher power rates, buses with larger batteries, or advanced technologies, such as inductive charging while in transit [26]. While more buses tend to increase queuing times, CABS could maintain more frequent service as more buses would be circulating on each line. Other models, such as battery swapping, may prove to be effective as well. The model we develop could further be used to study the feasibility of deploying electric vehicle fleets in other settings. Although we use a relatively simple vehicle energy model, more sophisticated models could be coupled with the simulation model we propose here. Moreover, the simulation model proposed here can also be used to study other alternative-fuel vehicle fleets, such as hydrogen-fueled vehicles. This analysis also neglects any life-cycle cost or emissions impacts of the charging station [27], which may affect our results.

Acknowledgments

References

References

[1] S. G. Wirasingha, N. Schofield, A. Emadi, Feasibility analysis of converting a Chicago Transit Authority (CTA) transit bus to a plug-in hybrid electric vehicle, in: 2010 IEEE 11th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Institute of Electrical and Electronics Engineers, Chicago, IL, USA, 2008.

[2] X. Wu, B. Cao, X. Li, J. Xu, X. Ren, Component sizing optimization of plug-in hybrid electric vehicles, Applied Energy 88 (2011) 799–804.

[3] C. Hatton, S. K. Beella, J. C. Brezet, Y. Wijnia, Charging Stations for Urban Settings the design of a product platform for electric vehicle infrastructure in Dutch cities, World Electric Vehicle Journal 3 (2009) 1–13.

[4] B. C. Langford, C. Cherry, Transitioning a bus transit fleet to hydrogen fuel: A case study of Knoxville Area Transit, International Journal of Hydrogen Energy 37 (2012) 2635–2643.

[5] A. Ip, S. Fong, E. Liu, Optimization for Allocating BEV Recharging Stations in Urban Areas by Using Hierarchical Clustering, in: 2010 6th International Conference on Advanced Information Management and Service (IMS), Seoul, South Korea, 2010.

[6] I. Frade, R. Anabela, G. Goncalves, A. P. Antunes, Optimal Location of Charging Stations for Electric Vehicles in a Neighborhood in Lisbon, Portugal, Transportation Research Record: Journal of the Transportation Research Board 2252 (2011) 91–98.

[7] L. Pelkmans, D. De Keukeleere, H. Bruneel, G. Lenaers, Influence of Vehicle Test Cycle Characteristics on Fuel Consumption and Emissions of City Buses, in: 2001 International Spring Fuels and Lubricants Meeting, SAE International, 2001.

[8] M. P. O'Keefe, K. Vertin, An Analysis of Hybrid Electric Propulsion Systems for Transit Buses, Tech. Rep. NREL/MP-540-32858, National Renewable Energy Laboratory (October 2002).

[9] L. Guzzella, A. Sciarretta, Vehicle Propulsion Systems: Introduction to Modeling and Optimization, Springer, New York, New York, 2005.

[10] I. Alcalá, A. Claudio, G. Guerrero, Test bench to emulate an electric vehicle through equivalent inertia and machine dc, in: 11th IEEE International Power Electronics Congress, Institute of Electrical and Electronics Engineers, Morelos, Mexico, 2008, pp. 198–203.

[11] J. M. Apsley, E. Varrone, N. Schofield, Hardware-in-the-loop evaluation of electric vehicle drives, in: 5th IET International Conference on Power Electronics, Machines and Drives, The Institution of Engineering and Technology, Brighton, United Kingdom, 2010.

[12] P. Fajri, R. Ahmadi, M. Ferdowsi, Equivalent Vehicle Rotational Inertia Used for Electric Vehicle Test Bench Dynamic Studies, in: 38th Annual Conference on IEEE Industrial Electronics Society, Institute of Electrical and Electronics Engineers, 2012, pp. 4115–4120.

[13] Z. Juda, Advanced batteries and supercapacitors for electric vehicle propulsion systems with kinetic energy recovery, Journal of KONES Powertrain and Transport 18 (2011) 165–171.

[14] Proterra, STURAA Test: 12 Year 500,000 Mile Bus from Proterra Model FCBE 35 (April 2009).

[15] J. P. Trovão, P. G. Pereirinha, H. M. Jorge, C. H. Antunes, A multi-level energy management system for multi-source electric vehicles—An integrated rule-based meta-heuristic approach, Applied Energy 105 (2013) 304–318.

[16] W. S. Wayne, N. N. Clark, R. D. Nine, D. Elefante, A comparison of emissions and fuel economy from hybrid-electric and conventional-drive transit buses, Energy and Fuels 18 (2004) 257–270.

[17] T. Imaseki, Japanese automotive transportation sectors impact upon Global warming, Applied Energy 59 (1998) 175–185.

[18] Environmental assessment of plug-in hybrid electric vehicles, volume 1: Nationwide greenhouse gas emissions, Tech. Rep. 1015325, Electric Power Research Institute, Palo Alto, CA, USA (2007).

[19] Environmental assessment of plug-in hybrid electric vehicles, volume 2: United states air quality analysis based on aeo-2006 assumptions for 2030, Tech. Rep. 1015325, Electric Power Research Institute, Palo Alto, CA, USA (2007).

[20] R. Sioshansi, P. Denholm, Emissions impacts and benefits of plug-in hybrid electric vehicles and vehicle to grid services, Environmental Science and Technology 43 (2009) 1199–1204.

[21] R. Sioshansi, R. Fagiani, V. Marano, Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power system, Energy Policy 38.

[22] R. T. Doucette, M. D. McCulloch, Modeling the prospects of plug-in hybrid electric vehicles to reduce CO_2 emissions, Applied Energy 88 (2011) 2315–2323.

[23] R. Sioshansi, J. Miller, Plug-in hybrid electric vehicles can be clean and economical in dirty power systems, Energy Policy 39 (2011) 6151–6161.

[24] W. Liu, W. Hu, H. Lund, Z. Chen, Electric vehicles and large-scale integration of wind power—The case of Inner Mongolia in China, Applied Energy 104 (2013) 445–456.

[25] A. S. Brouwer, T. Kuramochi, M. van den Broek, A. Faaij, Fulfilling the electricity demand of electric vehicles in the long term future: An evaluation of centralized and decentralized power supply systems, Applied Energy 107 (2013) 33–51.

[26] J. L. Villa, J. Sallán, A. Llombart, J. F. Sanz, Design of a high frequency Inductively Coupled Power Transfer system for electric vehicle battery charge, Applied Energy 86 (2009) 355–363.

[27] K. Nansai, S. Tohno, M. Kono, M. Kasahara, Y. Moriguchi, Life-cycle analysis of charging infrastructure for electric vehicles, Applied Energy 70 (2001) 251–265.
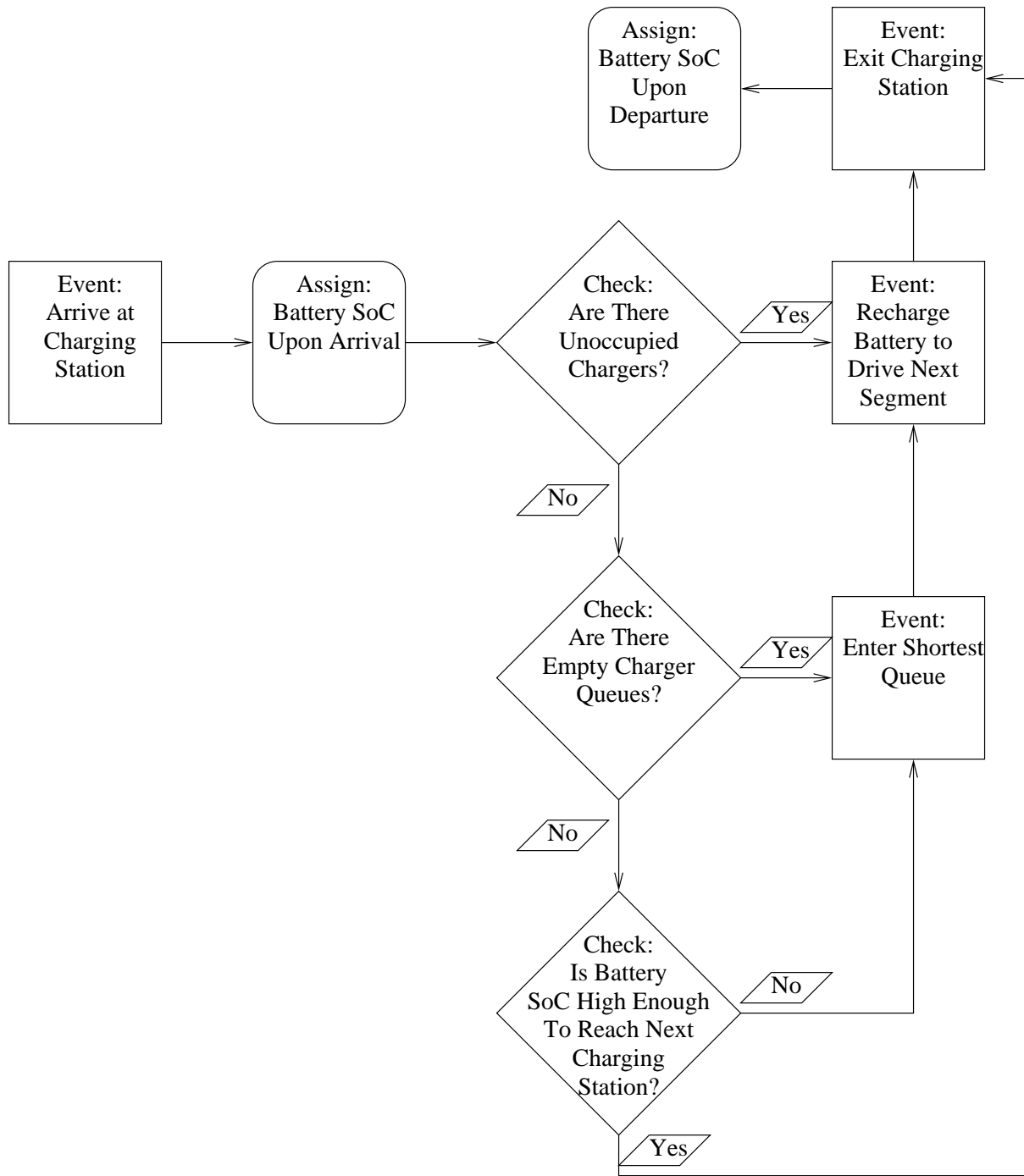
Event:
Arrive at
Charging
Station

Assign:
Battery SoC
Upon Arrival

Check:
Are There
Unoccupied
Chargers?

Yes

No

Check:
Are There
Empty Charger
Queues?

Yes

No

Check:
Is Battery
SoC High Enough
To Reach Next
Charging
Station?

No

Yes

Event:
Recharge
Battery to
Drive Next
Segment

Event:
Enter Shortest
Queue

Assign:
Battery SoC
Upon
Departure

Event:
Exit Charging
Station
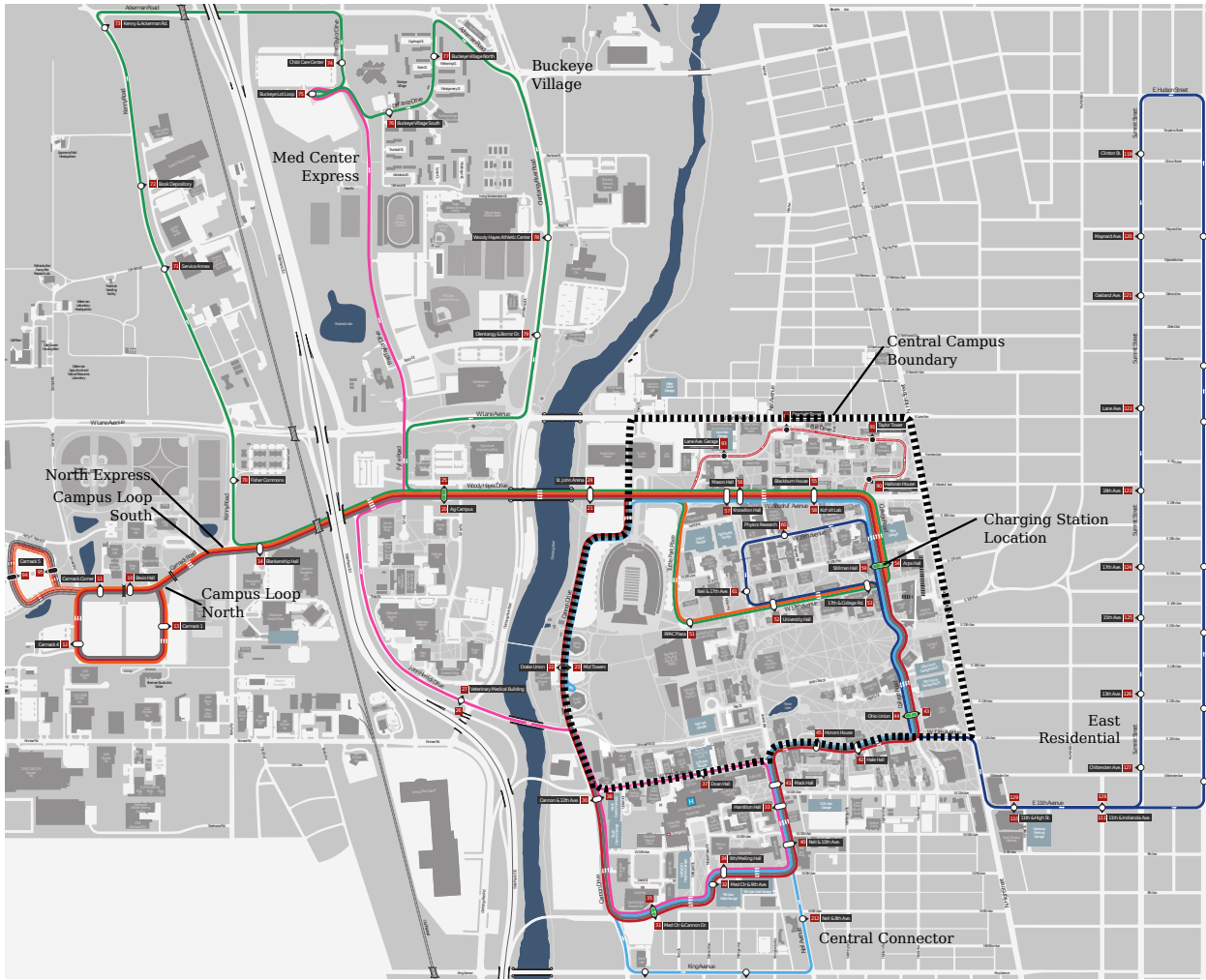
Figure 2: Simulation model schematic.

10

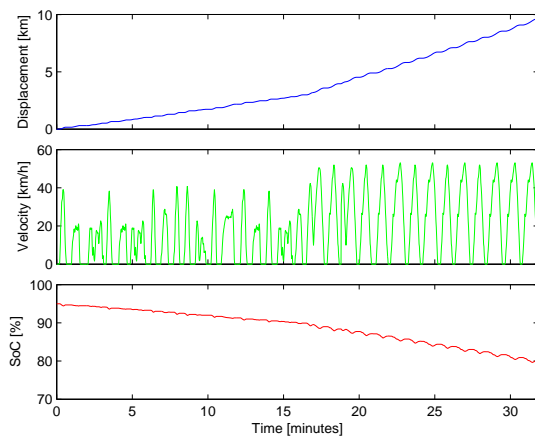Figure 3: Map of Campus Area Bus Service lines operating on the Ohio State University campus.

Figure 4: Simulated displacement, velocity, and SoC of CABS bus on the Campus Loop South line.

11