E-Transit-Bench: Simulation Platform for Analyzing Electric Public Transit Bus Fleet Operations

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ABSTRACT

When electrified transit systems make grid aware choices, improved social welfare is achieved by reducing grid stress, reducing system loss, and minimizing power quality issues. Electrifying transit fleet has numerous challenges like non availability of buses during charging, varying charging costs and so on, that are related the electric grid behavior. However, transit systems do not have access to the information about the co-evolution of the grid's power flow and therefore cannot account for the power grid's needs in its day-to-day operation. In this paper we propose a framework of transportation-grid co-simulation, analyzing the spatio-temporal interaction between the transit operations with electric buses and the power distribution grid. Real-world data for a day's traffic from Chattanooga city's transit system is simulated in SUMO and integrated with a realistic distribution grid simulation (using GridLAB-D) to understand the grid impact due to transit electrification. Charging information is obtained from the transportation simulation to feed into grid simulation to assess the impact of charging. We also discuss the impact to the grid with higher degree of transit electrification that further necessitates such an integrated transportation-grid co-simulation to operate the integrated system optimally. Our future work includes extending the platform for optimizing the charging and trip assignment operations.

CCS CONCEPTS

• **Computer systems organization → Embedded and cyber-physical systems**; • **Computing methodologies → Modeling and simulation**; • **General and reference** → *Cross-computing tools and techniques.*

KEYWORDS

Cyber-physical systems, traffic simulation, powergrid simulation, model-integration, co-simulation

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1 INTRODUCTION

Transportation in the modern world is responsible for extensive environmental impact, namely air pollution and emission of vast amounts of greenhouse gases, posing a severe threat to energy security. In the United States, the transportation sector accounts for 28% of the total energy use [11]. Transitioning to greater use of public transit systems can remarkably reduce energy use, thus providing a positive impact on society and the environment. However, even public transit systems require substantial amounts of energy; for example, public bus transit services in the US are responsible for at least 19.7 million metric tons of CO2 emission annually [17]. Electric vehicles (EVs) can have a much lower environmental impact than comparable internal combustion engine vehicles (ICEVs) [26] [27], especially in urban areas. However, in addition to the cost[1], the increasing electrification of transportation raises critical problems of the impact of EV charging on the power grid as well as the location and schedule of charging. This issue comprises several key concerns.

First, the locations of charging stations have to be strategically located to minimize nodal losses. Second, the electric utility operators have to balance the distribution network and estimate the daily needs considering the variation in demand. The service areas of the buses span major residential and commercial areas, which have already stressed electric supply feeders. Therefore, both a large number of buses charging at night in the depot (for low rates and minimizing disruption in transit) and individual buses charging en-route (at extremely high rates) can significantly affect grid reliability. For example, grid-agnostic charging assignments might result in power supply and demand imbalances, reduced power quality, excessive nodal losses, and price peaks. Since the charging times and locations of EVs drive this problem, it is imperative to understand the spatio-temporal interaction between mobility and the electric grid's distribution system. Third, the transit operators must also minimize the cost of charging EVs. Finally, the transit operators must also determine buses to trip assignments. The advantage of EVs over ICEVs depends on the route and time of day (e.g., the benefit of EVs is higher in slower traffic with frequent stops and lower on highways), hence the assignment can significantly affect energy usage and the environment [28].

Several efforts have attempted to manage the power grid along with route optimization and planning for the electric buses [23]

[1]EVs are also much more expensive than ICEVs – typically, diesel transit buses cost less than $500K, while electric ones cost more than $700K ($1M with charging infrastructure) [28].

[12] [34] [22]. However, these solutions are often decoupled. Large scale agent-based simulation platforms such as SUMO [18] and MATSim [16] have been crucial for planning future transportation scenarios, but they must be interfaced with micro-scale modeling systems for co-simulation with the power grid. For example, a system that works in this way can simulate a transit system using SUMO or MATSim and then analyze it in the context of the power distribution grid (e.g., using GridLAB-D [8]). Such a system can be used for integrated transit and power grid analysis (e.g., to analyze "a peak-day scenario where a major event in the downtown area leads to a sudden spike in demand on the transit system [13]. This not only constrains the road and transit systems but may cause a surge in power demand on the city's power distribution grid"). Further, it can also analyze the impact of different numbers of charging slots on the operating availability of electric vehicles.

In the past, we have developed Transit-Gym [30], a SUMO-based general-purpose transit simulator carefully calibrated for the city of Chattanooga, TN. This has been achieved by careful calibration of the underlying model. Note that for the simulator to remain viable, it is crucial to keep the physical transit network of the city and the simulated transit network in sync. Overall, the simulation engine is capable of providing road-based traffic measurement output, including macroscopic values such as the mean speed, the mean density, and the mean occupancy of road edge during specified time intervals. For each bus stop, we output the simulated schedule: time of arrival and departure, stopping place, and the number of persons that boarded and got off the bus. The passenger itineraries are configurable and are simulated based on input demand models provided by the local transportation planning office. For each transit vehicle, we can provide the current speed and acceleration

In this paper, we extend the Transit-Gym [30] and focus on bridging the gap between these two facets and develop an integrated simulation model that can replicate the complete functioning of the electric buses, their routes and charging schedules along with the real-time impact of charging them on the power grid. We demonstrate our system within the context of the city of Chattanooga. The system is designed such that the electric buses can dynamically interact with the power grid, causing changes in the grid load depending on whether they are charging or not. In this way, we can reliably perform integrated electric vehicle and electric grid simulations, and have a view of a complete scenario of buses moving along their route, getting discharged, stopping at the needed charging station, and recharging. The entire schedule of the vehicles can be simulated for any required period. Further, we can have improved simulation scenarios for the functioning of an electric vehicle, as the load on the power grid is an important factor to consider for charging all types of EVs. The effect on the power grid can be instantaneously generated in our simulated environment. Although this paper is limited to the discussion of the co-simulation environment, our ongoing work is focused on the optimization of transit trip plans and schedules for charging electric buses.

2 RELATED RESEARCH

It is important to emphasize that the overall problem is the integrated co-simulation and online optimization procedures that can address electric vehicle charging and route optimization while minimizing grid impact and transit operation costs. Pettet et al. [23] bring together optimizing bus charging for electric buses taking into consideration the grid load. The grid load is crucial to consider as it impacts the proper function of the entire electric grid of the city under consideration. Exacting too much from it may cause blackouts and additional infrastructure repairs. One of the crucial aspects of this model is the electric grid simulations. A simulation platform using Gridlab-D and smart grid sim is demonstrated by Hansen et al. in [15]. While it fails to take into account the optimizations of bus scheduling and grid loads, it provides a reference framework for the electrical simulations that are undertaken and is a fundamental example to show the integration between an electric simulator and the load balancing of a smart grid. The work provides a starting point for further simulation-based integrations.

Note though integrated transit and electric simulations are lacking, some works approach the charge scheduling problem entirely from the perspective of transit operations. For example, Paul and Yamada [22] provides a k-Greedy Algorithm-based approach for bus charge scheduling. Their work is one of the early efforts to address the issue of maximizing bus travel for each EV and in effect reducing emissions. Zhang et al. [34] use a bilevel optimization (using a genetic algorithm) to address the issue of the cost to operate electric vehicles by transit agencies. On the other hand, the extent to which the charger and battery configurations in an already existing environment can cope with a city's transit requirements is discussed by El-Taweel et al. in [12].

Another aspect of electric transit systems is the day ahead trading for bus depot operators to minimize the cost of electricity and battery degradation cost which has been addressed by Rafique et al. in [25]. It aims at minimizing the cost of electricity by using a two-stage multi-objective stochastic optimization technique based on a mixed-integer linear programming approach. The calculation of battery degradation is a vital cog in the operation of all EVs and the precise penalty cost for battery capacity degradation is added to the objective function to account for the exploitation of Vehicle Grid flexibilities. Similarly, Alizadeh et al. in [1] study collaborative and non-collaborative effects on pricing, when the owners of the vehicles are cooperating compared to when they are not - highlighting the improved benefits of cooperation(aggregation) of electric vehicle fleets. Lastly, there have been efforts to address the electric vehicle routing, optimization, and charging at a macro scale that studies this as an interdisciplinary problem to address the issue *economically*, *environmentally*, and to aid in *social welfare* [7, 10, 19].

However, most of these optimizations do not emphasize the need and the capability of coupled micro-simulations that can capture dynamics (node losses, surges, load loss) that will impact operations at the community scale. Further, the simulations are mostly focused on electric optimization. The movement of electric vehicles is not generally prioritized. The charge levels used are usually drawn off of energy estimates and the stochasticity introduced by the variation of degrading battery capacity and charging patterns is not clearly stated. This calls for the true integration of an electric and transit environment that will facilitate a smoother and more dynamic scenario for EVs to operate in and to locate, monitor, and instruct them.

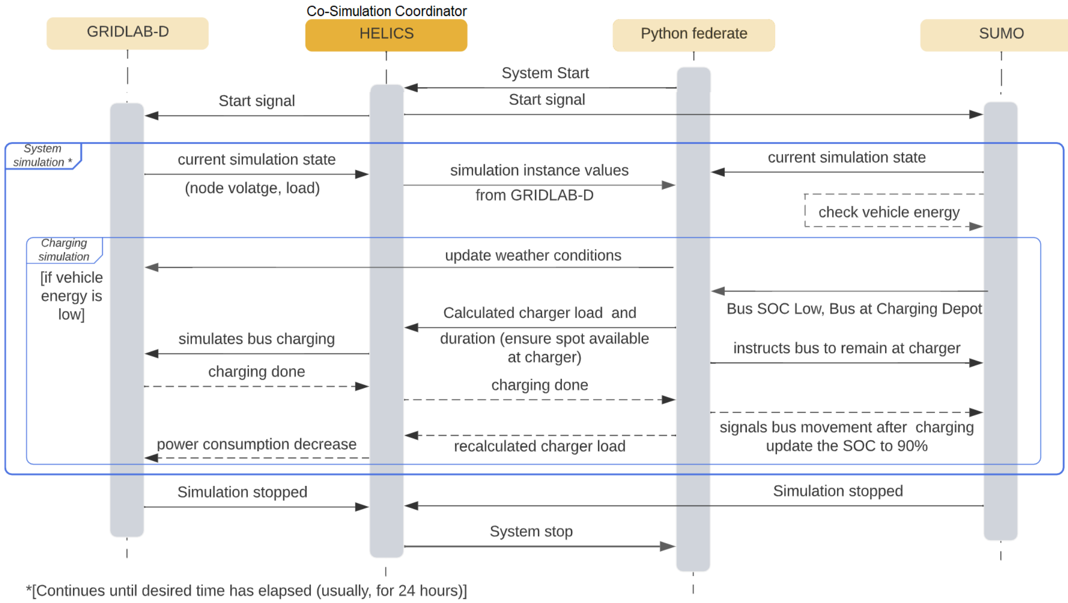


Figure 1: Sequence Diagram of co-simulation, describing the interaction between the transit and the power grid simulation

Our approach to solving this problem emphasizes the need for firmly grounding the simulation concepts within the performance as observed in the real world. Collecting and integrating multi-modal, spatiotemporal datasets is a challenging problem [33]. Our prior work with the city of Chattanooga developing approaches for assigning mixed-fleet vehicles to routes showed that operations teams can generate savings and reduce carbon emissions by optimizing scheduling [2], [28]. These optimization approaches require accurate predictive models of energy consumption [3]. It is also important to note that the energy consumption of various vehicle classes (such as electric, hybrid, and diesel) responds to covariates such as weather, traffic, and elevation differently [32].

Our previous work in multi-modal data collection, energy consumption model, and scheduling motivates the development of E-Transit-Bench. Specifically, we aim to provide an integrated Transportation-Grid simulation that can be used both in day-to-day scheduling and optimization as well as future planning.

3 OUR APPROACH

The integrated simulation is designed to make the individual underlying components work in unison, namely, the power grid simulation (using GridLAB-D) and the vehicle transit simulation (using SUMO). The information exchange that goes on between these simulators needs to be carefully handled as it is time-sensitive. This information exchange is performed with the use of the Hierarchical Engine for Large-scale Infrastructure Co-Simulation (HELICS) [21], an open-source co-simulation framework. The Co-simulator coordinator is responsible for time synchronization and acts as an agent between grid models in GridLAB-D and the python federate. There are dedicated computations modules programmed in Python to perform computations that interact with python federate, that utilize the various parameters or information from the interface. All of these components work in tandem and run the entire simulation platform synchronously. The work is described in Fig 1.

The co-simulation is based on a publish-subscribe model. GridLAB-D subscribes to the state of charge (SoC) values from the transit simulator when the EV arrives at the charging station. This translates to the grid as an additional load that follows a charging profile, predefined for the EV battery and the charger at the charging station. The charger profile is also season-dependent to ensure the charging time and the impact on the grid behavior are realistic. GridLAB-D publishes the parameters needed to compute the Grid Impact Score (GIS). Further expansion of the Transit-Grid co-simulation will include energy market decisions and also Transit systems scheduling that will add additional publications and subscriptions from the various entities being co-simulated. The details of the publish and subscribe mechanism applied to power grid simulation can be found in an application involving multiple federate integrated into a time-synchronized co-simulation in references [5, 6, 9].

The python federate is the instructor for all the other components, storing crucial instructions and passing them to the other components. The transit routes, power grid profiles, and other parameters are stored in memory for use by the respective simulators before the system is started. The Start message from the python federate instructs both the grid simulator and the transit simulator to begin their simulation cycles. This message is passed through the co-simulator coordinator onto the power grid simulator. The timestamps are synchronized for the execution to begin. The power grid starts generating its load and GIS and the transit sim emulate the movement of the buses on their designated routes and schedules.

The simulation goes on for the specified time duration. During this time, it can monitor the movement of all the individual vehicles (electric buses) as well as the state of charge (SoC) of the vehicles. The important checks that go on in the simulation are: (i) checking the SoC of electric buses and how much it has depleted, and (ii) checking for any changes in the grid load. The SoC of the bus drops as it moves around in its set route. When the SoC is below a critical level, then the bus needs to charge soon, else, it may run out of charge and stop in its tracks. We want to avoid that scenario and direct the bus to a charger as soon as possible. As soon as the bus moves on to the charging location and charging begins, its movements are stopped and the power consumption is added to the grid, in the grid simulation. The grid load is then measured throughout the period of charging the bus and can be done for multiple charging buses at a time. This is important as it provides an understanding of how much power is drawn from the grids at the charging stations and more importantly, how much the grid is affected by this usage and its effects on the surrounding neighborhoods.

Once the bus reaches the desired charge level, it is disconnected from the grid. The power draw at that charger is reduced to zero. The transit sim then resumes the movement of the bus along its planned route for the rest of the duration. This cycle can go on whenever the buses are low on a battery charge or are pre-planned to charge. Data about all the required parameters (like SoC, bus movement, weather, trips completed, and so on) can be collected and stored during this period. This technique helps us devise more efficient and battery-healthy bus routes.

The simulation ends when it has run for the desired duration. The python federate gets the message from both the grid simulator and the transit simulator that their execution has stopped. Subsequently, the federate performs any necessary post-processing on the collected data (like grid analysis, and bus efficiency). After these are performed, the program terminates, marking the end of the integrated simulation cycle.

3.1 Transit Simulation

The task of energy estimation for the electric buses requires us to know about the movement of these vehicles. It is necessary to know the time, location, route, speed, state of charge (SoC), and some other parameters of the vehicles, for proper measurements and calculations. The movement of vehicles is simulated using the transit-gym model [30]. The buses under consideration can be diesel-powered, diesel-electric hybrid, or electric-powered.

This section discusses the procedures undertaken to perform the simulations and generate the data required for further processing. We are trying to emulate the actual movement of buses for an entire day. The various steps undertaken during this simulation are shown.

3.1.1 Simulating a day's activity. The General Transit Feed Specification (GTFS) [20] provides the transit data for the specific day we want to simulate. This data contains the details about all of the transit buses that run during the day. It includes the concerned agency, the dates for the service to run, the different routes, the shapes forming the routes with their distances, the bus stops on each of the routes, the times when buses arrive and leave those stops, and most important - it contains all the trips per day that the agency plans to undertake with this schedule, indexed by trip id. This value can be filtered and changed to meet each day's demand by reducing the number of trips that are undertaken. A specific route may be traversed multiple times a day, going back and forth between the originating stop and destination stop.

The GTFS data can be further analyzed to produce comprehensive information about all the trips (aggregating the arrival times at stops, heading off the bus, its block id, and trip id). A block id implies the sequence of trips that the same vehicle has to make. There are other details that we want to incorporate into the model, by using the vehicle types used. The transportation demand is also modeled into the system to give an estimate of the number of people wanting to take the transit, along with the actual number of people that are getting on and off the bus. The Traffic Control Interface (TraCI) allows for controlling the SUMO simulator to extract detailed information.

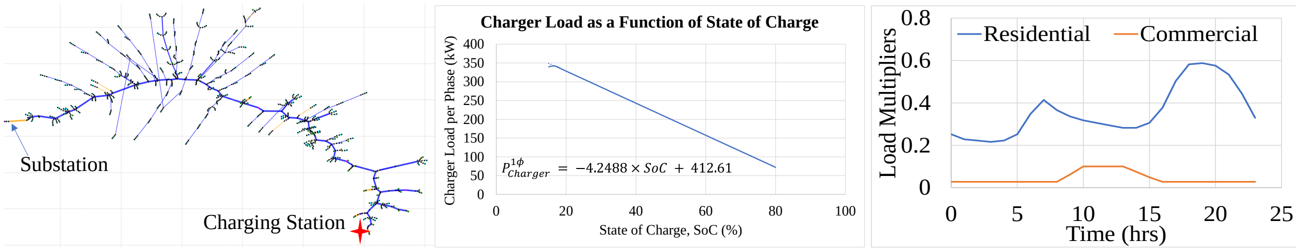
In the process, we want to generate the trips - their trajectory and the route paths being traversed (in the form of edges). Taking into consideration all these multiple factors discussed, we can feed them to our simulator (SUMO). The simulator can be configured to run for a set duration of time (most commonly, 24 hours).

The final step in this is to form the details of each trip that were earlier defined in the GTFS. The simulator generates results that consist of the unique trip id, bus types, bus stops, arrival and departure times, and the route that the trip served. The list of trips generated from the simulation successfully emulates the trips that would have been made by the transit agency during a specific day.

3.1.2 Energy Estimation. With all the trips generated, we need to know how much energy is used by each of the buses on the specific routes. Therefore, predictive models are required to estimate the vehicle's energy needs. As SUMO is a continuous, microscopic simulator the predictive models are also microscopic in nature. The microscopic models take as input distance covered, speed, acceleration, weather, and elevation change and predict energy consumed at one-second intervals. There are three classes of vehicles (diesel, hybrid and electric), each of which responds to the input features, and impacts the grid, differently [32]. Therefore, separate energy consumption models are trained for each of the three-vehicle classes. The energy models are built on artificial neural networks, in accordance with current state-of-the-art [2]. Energy demands at the trip level are derived by aggregating predictions along with the scheduled trips in GTFS.

Each of the trips is processed through its respective model and its speed, acceleration, distance covered, time taken, and weather conditions are analyzed. These parameters help define the total energy consumption for each trip. As one bus may travel multiple trips (denoted by the same block id), the cumulative energy use can also be measured for the entire day's running for the bus. The trips generated here contain a mix of ICE buses and electric buses. For ICE buses, the energy use is in gallons of fuel consumed. For the electric buses, the total energy used by them is considered in terms of kWh (kilowatt-hours). Since our primary focus is on electric buses, we separate them from the rest and continue further analysis, such as finding the grid impact score (it is detailed in further sections).

The total energy use, in turn, is used to generate the state of charge (SoC) metric. SoC is the primary metric of concern - low SoC indicates the bus needs to be charged soon. An electric bus usually starts the day's first trip with a high SoC (almost 90% of its



(a) (b) (c)

Figure 2: (a) Taxonomy Feeder Model with Charger Location. (b) Load induced on charger when charged from a specific State of Charge. (c) 24-hr external load on the simulated power grid.

battery capacity). It gradually uses up the battery's energy throughout the day's trip, lowering its SoC. Thus, we can estimate the SoC of the electric buses from the simulated results, which can be further provided to the grid simulator, to perform the de-coupled co-simulation.

Next, we describe the case study from our partner community in Chattanooga that will be useful in understanding the simulation operation. Then, we proceed to discuss the various steps involved in the grid simulations and incorporate the information from the Transit simulations into the EV or electric bus charging and analyze its impact on the grid behavior. This section also provides the details of quantifying the impact of EV charging on the grid performance through a formulated grid impact score that includes the voltage measurements, losses in the system, and total distribution system load.

3.2 Case study of Chattanooga

In our simulation environment, the data is obtained from the Chattanooga Area Regional Transportation Authority (CARTA). The GTFS generated is from the actual day's trips for Jan 11, 2022, for 24 hours, from 12 AM to 11:59 PM. This data contains the various trips and the associated buses. To model the grid aspect (discussed in the next section) we use a taxonomy feeder with 265 nodes (R5-12.47-1) and a root node voltage of 13.8 kV that includes overhead lines, underground cables, triplex lines, and triplex meters. The medium voltage parts of the distribution feeder at the primary and secondary distribution systems are usually modeled using overhead lines and underground cables. These parts of the network feed the large commercial loads and tertiary distribution networks, where the terminal loads are located. The terminal connections to the low voltage consumer loads at the residential level are usually connected using triplex lines and the corresponding meters at such nodes in the distribution feeder are called triplex meters. The feeder represents a sub-urban and urban feeder section that has potential connectivity to other feeders and models the representative architecture from Chattanooga[2]. The structure of the feeder is shown in Fig 2a. The feeder structure is similar to the real feeder profile of the Chattanooga region and hence is chosen for the present analysis.

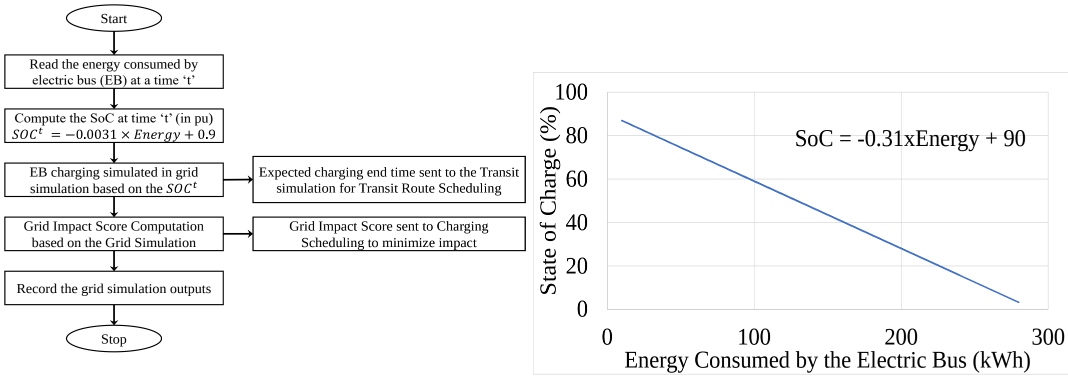
3.2.1 Distribution Grid Components. Transportation electrification has a direct relation to power grid operations. The EV charging can cause sudden spikes of load increase in the distribution grid that can cause issues like imbalance, increased losses in the network, and drop-in voltages due to the increased load. The location of the charger along with the amount of charging load should be considered along with the detailed grid models to evaluate the grid impact accurately.

In the current work, the location of the charger is chosen to be closest to the largest load in the system mimicking a large commercial location[3]. The charging station is modeled with two chargers. The simulation of the electric bus and its impact on the grid is considered with a winter seasonal profile and a corresponding charging profile is considered, based on the charging loads given in reference [4]. The charger load on the grid is determined by a linear function (an approximation based on data presented in [4]). This load function (Fig. 2b) describes the expected increase in the load per phase on the grid when the EV gets charged. This exercise can be repeated for advanced chargers and improved charging profiles too, and the developed framework can easily integrate it into the power grid models through the load that is reflected on the grid during a charging event. Fig. 2b also gives the charger load per phase and the derived 3-phase charger load function. The peak 3-phase load due to the charger ($P^{3\phi}_{Charger}$) is approximately 1 MW for a single charger at the charging station. The charging current and the charging power depend on the SoC of the battery when it is charging. This profile is different for different kinds of batteries and chargers. Based on the data available in reference [4], an average linear approximation is constructed that is used to model the increase in the load on the distribution system as a function of the SoC of the battery. Depending on the charging station models, the rate of charging and the load on the grid can be modeled. These are also dependent on the season, the charging time is slower in winter as compared to summer.

The loads in the power distribution feeder are modeled with two load profiles: commercial; and residential load profiles. The largest 3-phase balanced loads in the feeder are modeled as commercial loads. The remaining loads in the feeder are modeled as residential loads with a residential load profile. The commercial and residential load profiles are also considered for the winter season and shown in Fig. 2c. These load profiles for the loads are assumed for a typical weekday in winter in the US.

[2]The actual city feeder architecture is security-critical and cannot be shared publicly

[3]In future work, we will work on optimizing the location based on the analysis enabled by the co-simulation discussed in this paper.



(a) **(b)**

Figure 3: (a) Overall steps to integrate the transportation and energy simulations.(b) The Transit system provides energy used at every instant. We use the following linear function to estimate the SoC (this is calibrated for the electrical vehicles in Chattanooga Fleet.).

3.3 Modeling and Simulating the Impact on Electric Grid

Note the electric simulation used in this study (as implemented by GridLAB-D) is a quasi-steady-state time series analysis with an unbalanced distribution system power flow at every second. This simulation is configured with the feeder described in the previous section and configured with weather profiles from the city. The steps involved in utilizing the Transit simulation output to simulate the charging of the electric buses for the corresponding SoC and time are described in the flowchart shown in Fig. 3a. Estimating the SoC based on total energy consumed is one important step in the present decoupled co-simulation analysis. The Transit simulation records the energy consumed in every trip along with the amount of discharge of the battery (in terms of a drop in SoC with respect to full charge). This information is represented through a linear regression fit using all the discharge and energy consumption values for all trips simulated for a day in the Transit simulations. The resultant linear function is shown in Fig. 3b. Using the SoC-Energy relation, the end SoC is computed for every electric bus in simulation at the end of its day's trip or when SoC reached values in a range of 15% − 20%.

3.4 Grid Impact Score

A key aspect of our analysis is the generation of grid impact score (GIS) which is a modified version of the grid score introduced in [24]. This requires collation of charging load, daily load, and load flow analysis is performed to monitor nodal voltage deviations, phase imbalances, line losses, and the apparent power drawn from the feeder head to analyze equipment thermal loading. These measurements are:

- Nodal voltage deviation of the phases $\phi \in \{a, b, c\}$,

$$\Delta v_{i,\phi} = \frac{v_{i,\phi} - v_{nom}}{v_{nom}} \tag{1}$$

- Imbalance factor [31] of the circuit after charging at node i at time t approximated by

$$\mathcal{I}_i = \frac{v_2}{v_1} \approx \sqrt{\frac{1 - \sqrt{3 - 6\alpha}}{1 + \sqrt{3 + 6\alpha}}}, \tag{2}$$

where,

$$\alpha = \frac{v_{ab}^4 + v_{bc}^4 + v_{ca}^4}{(v_{ab}^2 + v_{bc}^2 + v_{ca}^2)^2}, \tag{3}$$

and v_1 and v_2 are the positive and negative sequence voltage, and v_{ab}, v_{bc}, v_{ca} are the phase voltages corresponding to the phases ab, bc, ca.

- Total line losses L in underground cables (L^{ug}), overhead lines (L^{oh}) and triplex lines (L^{tx})after charging in the distribution feeder for charger at node i,

$$L_i = L_i^{ug} + L_i^{oh} + L_i^{tx} \tag{4}$$

- Apparent power drawn from the feeder head (substation) f corresponding to the node i where the charger is placed at time t,

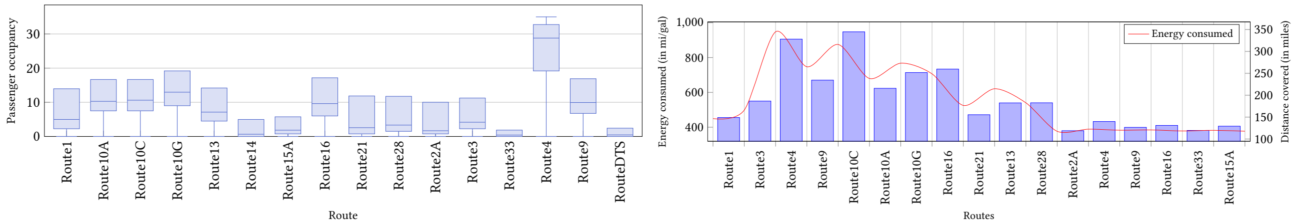
$$\mathbb{S}_f = \sum_{\phi} V_{f,\phi} I_{f,\phi}, \quad \forall \phi \tag{5}$$

where, the complex voltage and current at the feeder f are denoted by V_f and I_f.

Now, we introduce a novel metric to measure the impact on grid. This grid impact score(GIS) g_i is given by,

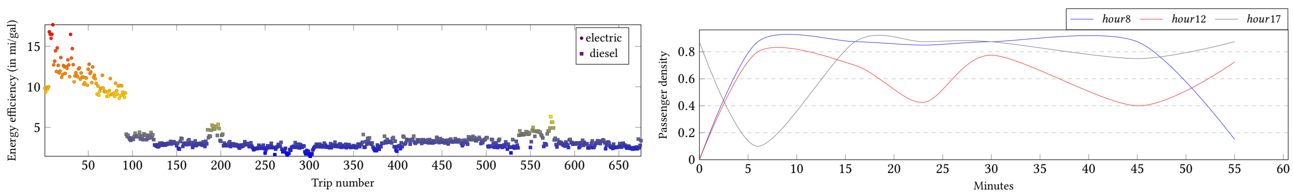
$$g_i = \frac{1}{\sum_n w_n} \Bigg[w_1 \sum_{j \in \phi} \frac{1}{3} \frac{|\Delta v_{i,j}|}{\Delta v_{max}} + w_2 \frac{\mathcal{I}_i}{\mathcal{I}_{max}} + w_3 \frac{Re\{L_i\}}{Re\{L_{max}\}} + w_4 \frac{Re\{\mathbb{S}_f\}}{Re\{\mathbb{S}_{max}^{sub}\}} \Bigg] \tag{6}$$

Here, Δv_{max}, $\mathcal{I}_{max}$, L_{max}, $\mathbb{S}_{max}^{sub}$ denote the maximum allowable limits of nodal voltage deviation, imbalance factor, total system loss and the apparent power drawn, respectively. Based on the above measurands in (2)-(5), a novel grid score metric of charging at node



(a) (b)

Figure 4: Results from the transit simulation for a day in January in Chattanooga. (a) Maximum passenger occupancy of each bus along the bus stops by routes over 24 hours. (b) Energy consumed rates (in gallon) and the total distance travelled across trips on each route.



(a) (b)

Figure 5: Results from the transit simulation for a day in January in Chattanooga. (a) Energy efficiency of vehicles across trips. In general, electric vehicles are most efficient. But there are places where diesel vehicles are more efficient. This points to a need for optimizing trip assignment [28]. (b) Distributions of bus occupancy at specific hours on route 4.

i at time t is defined, where, $w_n, \ \forall n \in \{1, 2, 3, 4\}$'s are the various weights associated with the additive terms in (6) (normalized voltage violation, imbalance factor, loss, and apparent power drawn at feeder's head). These weights are introduced so that the planner can choose to prioritize each contributing factor in the metric differently. Uniform contribution from the contributing factors would require each weight to be equal to 1. The joint grid score of multiple chargers' charging impact at a particular time can be derived using an extension of the expression in (6). The time variable t is dropped for simplicity in the above derivation. The purpose of introducing the grid impact score is it include in the planning and operation decisions of the grid. This would enable the transit to make grid-friendly choices resulting in reduced loss (otherwise to be borne by all the users), and power quality issues and would aid in different infrastructure upgrades benefiting everyone.

4 CASE STUDY

The simulator and its working are put to test here, as we discuss simulating the operations of the electric buses and the effect on the electric grid due to charging them. We look into two scenarios - first, for a regular day's traffic for the present day. The second case is for the forecasted use of electric vehicles, as the EV load on the grid is projected to be 15-30% of the total capacity, by 2050 [29]. The figures in our modeled assumptions are not far away from the expected rise.

4.1 Analysis of the day of operation

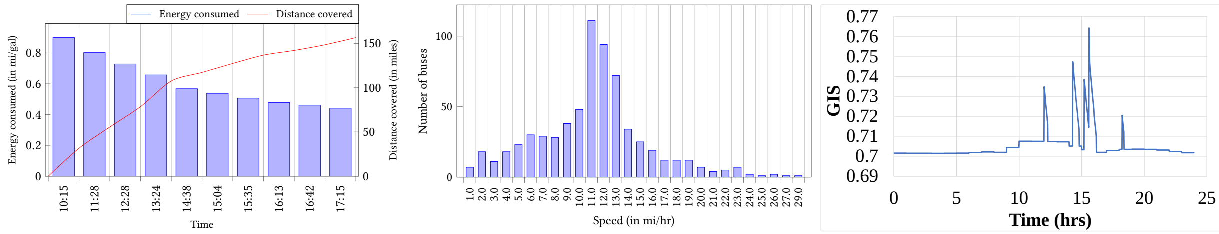
We now introduce the analysis of a day from January 11, 2022, as described in Section 3.2. The traffic and trip data are generated for the provided GTFS (obtained from the local transit agency), to find the energy usage for the electric buses. Figure 4a shows the maximum passenger occupancy across all trips grouped by routes. Figure 5b shows the aggregated passenger density. Figure 5a describes the energy efficiency in miles per gallon (we convert the kWh from electric vehicles to gallons per mile - this is done according to the standard conversion factor as defined by the United States Environmental Protection Agency [4]) Figure 4b shows the cumulative energy consumed and distance traveled across all trips on each route.

Table 1: Summary of five different charging scenarios that were simulated

Bus #	SoC at Charging Instant (%)	Charging Start Time	Charging End Time
1	49.93	12:00	12:18
2	24.30	14:17	14:47
3	33.65	15:12	15:38
4	15.68	15:35	16:11
5	66.75	18:14	18:23

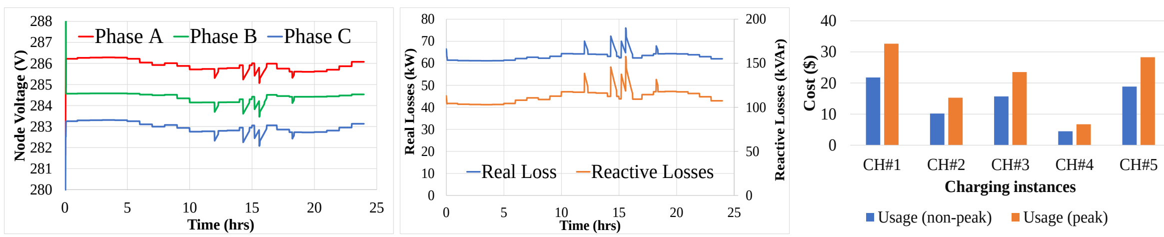
The energy estimator runs through all the generated trips according to the steps discussed earlier. It can provide a comprehensive consumption metric not only for each trip, but also for blocks of trips, and for each vehicle that ran. The SoCs for the electric vehicles are then generated (Fig. 6a) and made available to the grid simulator for analysis of the GIS. The average speed of the electric buses is shown in Fig. 6b. During the simulation, we constantly check the SoC of the vehicles and then estimate when the vehicle is

[4] https://www3.epa.gov/otaq/gvg/learn-more-technology.htm



(a) (b) (c)

Figure 6: Results from the transit simulation for a day in January in Chattanooga. (a) SoC change for one bus with sequential trips. (b) Average speed of the electric buses across all trips for 24 hours (c) Grid Impact Score across 24 hrs.



(a) (b) (c)

Figure 7: Results from the transit simulation for a day in January in Chattanooga. (a) Node Voltage at the charger location. (b) Total Feeder Loss (c) Usage charge breakdown in 5 charging instances (Table 1).

ready for charging (once it finishes its trip in the transit simulation). Table 1 shows the summary of the inputs to one of the simulations discussed in Section 4.1. The end SoC for each bus is assumed to be 80% of its capacity. For the time duration between 15:35 hours to 15:38 hours, both the chargers at the charging station are actively charging the buses and during the rest of the charging cycles, only one charger at the charging station is actively charging based on the schedule of the Transit system. The grid simulation results are summarized below. Figures 7a and 7b demonstrate the impact of charging on the grid performance. The results show the voltage at the charging node and the total feeder losses. The voltage dips during charging due to an increase in the load and since the charger is located at the end of the feeder the loss increase in the system during the charging times can be observed clearly.

A grid impact score (GIS) is determined for the given scenario and location of the charger. This GIS will depend on various parameters like the location of the charger, seasonal impact on the charging profile, etc. For the presented simple case of low penetration of electric buses that has five electric buses charging at various times that are modeled in a 24-hour day-long simulation, the GIS is computed and its variation in 24 hours duration is shown in Fig. 6c. The GIS is relatively higher during charging (compared to the instant just before charging) as there is a significant drop in voltage and an increase in the system losses.

However, as other electric vehicles in the city are considered and modeled to be charged in the area at the same time, the GIS would be much higher. A hypothetical case of high penetration of electrical vehicles is described next.

4.2 Impact of additional electrical vehicles

For this part of the study, we estimate the presence of additional electric vehicles that are charging in the vicinity. To analyze this, the charging loads for the previous scenario are increased by 10 times. In this scenario, the GIS increases and may cause serious disruption to the grid. Fig. 8c shows the comparison of the GIS and how it increases under high penetration of other electrical vehicles considering no other changes in the grid models. However, with the evolving grid-edge technologies like real-time retail market designs, and increased integration of renewable energy sources (RES), the GIS is expected to be significantly higher. The deviation terms in the GIS formulation are usually normalized by the maximum allowable deviation - corresponding to each of the factors (e.g., voltage, loss, etc). Thus, in case of no grid-related constraint violation, its value should be within 0 and 1. However, in this case, the normalization factor is chosen to be the maximum observed deviation in the lower EV penetration scenario for ease of comparison. Therefore, in this paper, the GIS value is allowed to exceed 1. In case of using the framework for the charging optimization problem in the future, the high penetration scenario is likely to cause constraint violations leading to GIS values exceeding 1, and thus such scenarios would be discarded.

Note that the Grid Impact Score (GIS) is a reflection of grid performance parameters like voltages, systems losses, etc. Figures 8a and 8b shows the impact of high penetration of electrical vehicles and the integration of the charging infrastructure with the grid. The losses and the voltage drop in the system are more profound in this case, however, these can be addressed by optimally scheduling the EV (in our case, electric bus) charging to distribute these peaks

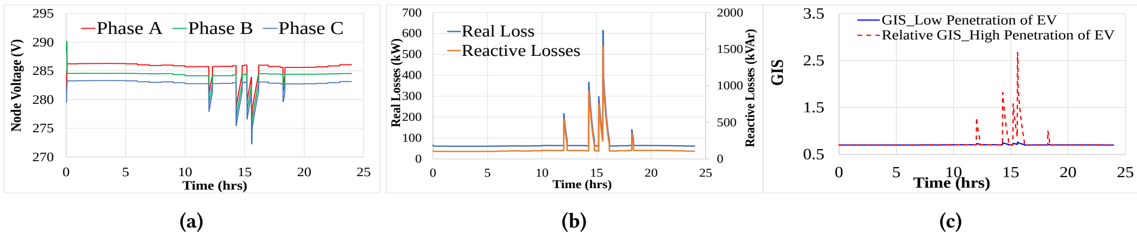


Figure 8: The figures show results of the impact on Grid when consider the load induced by additional transit vehicles. (a)Node Voltage Magnitudes at Charger Location. (b)Total Feeder Loss (c) GIS under High Penetration of EV Charging Relative to Low EV Penetration Case.

caused by the sudden increase in the charging loads. The GIS used for these computations can be utilized as an indicator for determining the optimal operation of the integrated transit-grid systems. These results indicate that considering various kinds of distributed energy resources (DERs) along with large-scale electrification of transportation will impact the grid behavior and will need coordinated efforts to avoid unwanted disruptions to the operations of the transportation and the grid infrastructure.

4.3 Charging Cost

CARTA and the electric utility's rate structure are used to obtain the cost of the charging model. The total cost of electricity for recharging a bus's battery does not only depend on how much energy is consumed from the grid but also, on the rate at which energy is drawn, i.e., power (kilowatts). The distribution utility (EPB) bills two types of charges a large customer-usage charge and a demand charge. The usage charge is proportional to the energy used. This rate varies from peak to non-peak hours. Moreover, the peak hours vary in season. The demand charge is proportional to a portion of power drawn and applies only if it aggravates the peak load. Based on EPB's rates structure for commercial, government, and industrial consumers, as shown in the GSA-2 rate [14], the worst case and best-case costs for recharging the buses during the stated times would be following as shown in Table 2. In addition to the rate structure outlined in GSA-2, to introduce a time-of-use usage charge, the peak time usage charge is assumed to be 1.5 times the non-peak usage charge. The usage charge breakdown of the charging instance shown in Table 2 is shown in Fig. 7c. The demand charge for any of the instances, if applied, would be $5886.

Table 2: Electric Bus Charging Cost

Case	Usage Charge ($)	Demand Charge ($)
Best case (non-peak)	71	0
Worst case (peak)	106	5886

4.4 Discussion

The electrified transit operates in tandem with the underlying grid system. However, electrified transit's day-to-day operation often does not consider the grid's health. The transportation system also has limited visibility into the grid. Some grid-related preferences are baked into the offline, coarse pricing model of the charging. This leaves room for additional improvement in planning and operation that would be optimal for both systems. The framework of the transportation-grid model presented in the paper provides additional knobs for the integrated transit-grid system to account for bringing greater social welfare by achieving the following goals:

- *Reduced loss:* As we can observe from Fig. 8b, the loss is often significant due to the event of charging for the high penetration of electric bus charging scenario. The loss also varies from node to node. Any additional loss occurring in the system burdens not only the EV fleet owner but all the customers by driving the cost of production up.
- *Scaling down infrastructure upgrade cost:* By considering GIS into a scheduling algorithm, infrastructure upgrades could be scaled down, in the process bringing additional benefits for the customers by allowing for lower transportation costs.
- *Absorbing solar energy:* The framework is also capable of integrating weather-dependent distributed energy resources models in the form of high solar energy scenarios, encouraging charging during these peak production hours.
  Enabling all of the above with the framework would ensure that increased social benefit is achieved when the two entities (the power grid and the transit agency) cooperate.

5 CONCLUSION

Electrification of the transit fleet provides numerous societal benefits including a reduction in greenhouse gas emissions, reduced cost, and improved environmental health. However, owing to the substantial need to charge electric buses, it can cause major imbalances in power supply and demand leading to grid instability. Therefore, in this paper, we presented a grid-aware approach and a simulation platform that can co-evaluate the grid impact of an electrified transit system. A framework is presented to combine detailed, agent-based simulations of public transportation, and the power flow of the power grid distribution system. Both the systems independently represent realistic daily conditions such as the transit's traffic flow, energy use, schedules, etc. for the transportation systems and also for power flow occurring due to nodal demands at the distribution systems. The systems interact and influence each other with a common point of coupling taking place when the charging of buses takes place. We further validated our experiments using real world data and presented a detailed case study to demonstrate our approach. The initial results presented here show how we can capture and quantify several charging events' impacts on the grid to further optimize the integrated operation. This framework can further be used for developing and testing algorithms for grid-aware transit operations. The framework is capable of including customized charging profiles making it future proof to account for newer charger models and improved charging profiles that reflect as the load on the grid. The GIS can be used as a metric in future optimal charging solution methods where it can reflect on the feasible and infeasible regions for optimal charging. In the future, we also plan to work on developing a decision agent in our platform that uses machine learning techniques for optimizing the charging and trip assignment operations.

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