# Developing a Large-Scale Microscopic Model of Electric Public Bus Operation and Charging

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***Abstract*—The pace of electric bus deployment is increasing rapidly worldwide. Transportation agencies and bus operators are faced with the challenges of re-evaluating the dimensioning of their bus fleet and the associated charging infrastructure with the introduction of electric buses. This paper introduces a new agent-based public transport simulation model currently being developed and based on a general-purpose microscopic traffic simulation platform. It enables users to conduct city-scale studies and analysis of the day-to-day operation of a public bus fleet of traditional and electric buses, including detailed modelling of charging stations, termini and depots. Results are presented in a case study to electrify the entire bus fleet of Singapore.**

***Index Terms*—electric buses, agent-based simulation, charging infrastructure, public transport**

## I. Introduction

Continuous growth and rising urbanisation of the population increases the pressure on urban transportation systems. In addition, climate change as well as local air pollution concerns motivate the automotive industry towards cleaner vehicle solutions, in particular electric vehicles (EV). While the penetration of EVs in the private vehicle sector is relatively slow and will extend over multiple decades ([1] estimated that by 2040 only one third of the global light duty vehicle fleet will be composed of EVs), the public transportation sector is already experiencing signs of a much faster transition towards partially or fully electrified public bus networks [2]. Major cities such as Shenzhen or Shangqiu have already taken the lead and replaced their entire bus fleet with electric buses (EB) while cities such as Los Angeles or Paris intend to do the same by 2030 or earlier [2]. Many others are only starting to procure EBs and are trialling their deployment to gain better knowledge of the specificities and consideration required for their operation [3]. In the recent years, many studies have investigated the feasibility and the benefits of EBs for public transit. These studies can be categorised as (i) case studies using high-resolution velocity measurements applied to selected bus routes or on a small public transport network or using standard driving profiles [4]–[6] or (ii) models based on average energy demand value directly proportional to distance or time [7]–[10]. In the first case, it is challenging to scale the model to larger bus networks while at the same time taking into account the characteristics of each bus route (due to the high amount of data to be gathered), while in the second case the models are easily scalable to larger areas but lack the heterogeneity of real-world bus operation.

In this paper, we introduce a newly developed agent-based, city-scale model of electric public bus operation and bus charging based on a microscopic traffic simulation platform. The model is described and preliminary results based on the current version are presented in a case study for Singapore. While both microscopic modelling of electric bus driving [11] or large-scale modelling of charging infrastructure for electric buses [10] have been studied previously, the model and results presented in this work represent to the best of our knowledge the first attempt at combining both approaches simultaneously in a single software platform without relying on standard driving profiles or high-resolution measurements as required input data. This model enables to study in high details the energy demand and charging infrastructure requirements for the electrification of public transport network at large scale while taking into account the heterogeneity of the various bus services.

## II. Model description

### A. The CityMoS platform

The scenario was implemented on the City Mobility Simulator platform (CityMoS) [12], [13], a microscopic agent-based discrete event simulation platform currently developed by research teams at TUMCREATE. The development of CityMoS started as a generic microscopic traffic simulator for cars, providing a flexible platform for research on agent-based traffic modelling. Subsequently, an extension for public bus operation was added to the platform. This public transport extension added infrastructure such as bus routes, bus stops, termini and depots as well as behaviour models to dispatch buses in order to serve the bus routes, dwell at bus stops and pick-up passengers. More recently, the models in CityMoS were extended again to model the operation of electric buses and their charging infrastructure more specifically.

The CityMoS platform is developed in C++ with a modular architecture that focuses on high-performance execution, advanced models for vehicle components and driver behaviour. Time in the simulation is discretised to the millisecond level and the inter-event time for updating the position of the agents is configurable by the user. In the following, it was set to 250 ms.

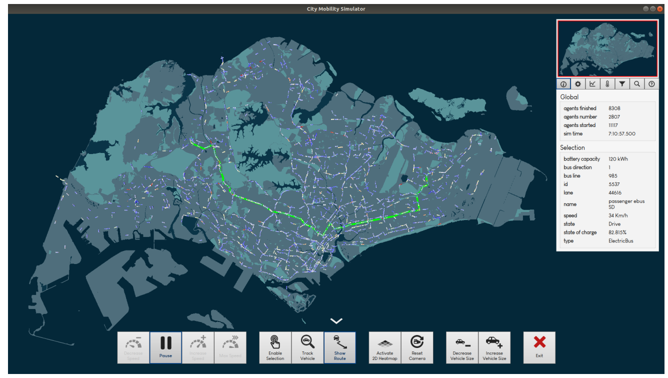
Traffic simulations in CityMoS consist of three main parts: (i) infrastructure: including road and routing network, bus stops, bus termini, bus depots and charging infrastructure;

*Author's version submitted to IEEE VPPC 2019 conference on 2019-07-29. Please check for updates at* `https://zr.k.vu/GalletEtAl2019`

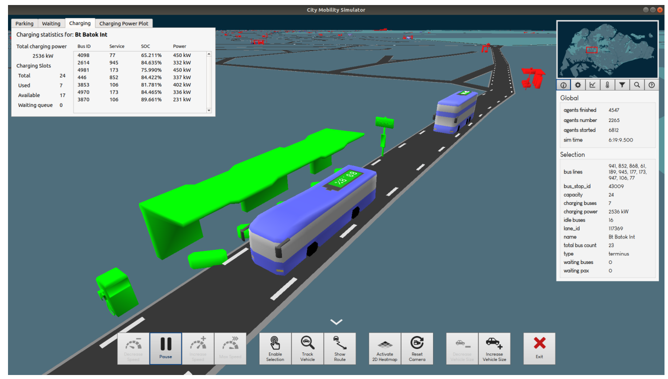
(ii) Driver-Vehicle Units (DVU): a combination of a *driver behaviour model*, which controls the behaviour of the agent on the road, and a *vehicle model*, which determine the vehicle characteristics; (iii) other behaviour models: they define the other interactions between the agents and the infrastructure (e.g. charging behaviour, dwelling behaviour).

A driver behaviour model is composed of sub-models including car following, lane changing, charging behaviour (for electric agents) and dwelling behaviour models (for public transport agents). The car following and lane changing models are responsible for calculating the desired speed and acceleration of the agent and deciding when and how fast to change lanes, while taking into account the position and movement of other agents (road traffic) and the environment (e.g. length of road ahead, traffic lights). A vehicle model is composed of a vehicle characteristics model (such as length, weight, drag coefficient, rolling resistance, ...), a powertrain model (modelling the efficiency and physical limitations of the powertrain) and, for electric vehicles, a battery model.

In addition to the agent-based simulation core, a 3D interface is available to provide real-time inspection and interaction with the simulation. The screen captures shown in Fig. 1 illustrate both the scale of the simulation (Fig. 1a) and the aspect of microscopic agent-based models (Fig. 1b). The simulation can be run on hardware ranging from laptops for simple studies to high-performance computing clusters for very large and detailed scenarios. As an example, the case study presented in the following can be run on a laptop with 16 GB of RAM.



(a) Example of city-scale simulation, with one bus route highlighted



(b) Close-up showing two electric bus agents, a charging station (in green) and a bus stop (in red)

Fig. 1. Screen captures of CityMoS3D.

### B. Bus operation model

Buses in the simulation are assigned to bus routes which are a sequence of road links that the buses have to follow. Each bus departs from its departure terminus. When a bus reaches a bus stop on its route, a dwelling model slows down the bus and lets it dwell to pick up passengers before departing again. Upon reaching the end of the bus route, the bus enters the destination terminus to be parked (and optionally recharged for electric buses) until the next departure. Bus depots are also modelled. Both bus depots and termini have a limited bus parking capacity. Thus, when a terminus requires more buses, these will be dispatched from a depot. Conversely, when too many buses are parked in a terminus, some of them will be sent back to depots. The off-service trips between bus termini and depots are also known as dead-heading trips.

### C. Electric bus model and charging model

The instantaneous mechanical energy demand of DVUs is calculated based on a common longitudinal dynamics model formulation. The forces related to acceleration, velocity, air drag, rolling resistance and road inclination are computed at at every time step. The powertrain provides the mechanical force required to fulfil the desired acceleration and velocity (as computed by the driving model) and calculates the energy consumed. For electric buses, the powertrain consists of a battery, an inverter and an electric motor. The losses in the inverter and the electric motor are modelled by means of two efficiency maps based on the motor speed and torque. Additionally, a heating ventilation and air conditioning (HVAC) model is also included and contributes to the energy demand calculation. At each time step, the power and energy to be drawn from (or injected into during energy recuperation while breaking) the battery is applied and the state of charge (SOC) is updated.

Bus depots and termini can be equipped with charging stations. This enables electric buses in the simulation to perform *end-station* or *overnight* charging. A charging station consists of one or more chargers. Each charger has a nominal maximum power it can deliver. The chargers are shared among all electric buses in a charging station. When an electric bus completes a trip and arrives at a destination terminus or depot equipped with a charging station, the bus will enter the charging station if it requires charging. If there is an available charger, the bus will start charging immediately. Otherwise, the bus is placed in a waiting queue. As soon as a charging point becomes available again, a selection algorithm picks a bus from the waiting queue and the selected bus is allowed to recharge. Before choosing an electric bus for a trip departure, the SOC of the bus is checked to ensure that the bus has sufficient energy to complete the given bus route.

Different charging behaviour models can be implemented and compared. At the current stage of development of the model, a few simple, rule-based algorithms have been implemented. They take decisions such as selecting which bus from the waiting queue to pick next, which bus to send next when a trip must start, which bus to select for sending back to a depot, etc. These algorithms include presently: random, first-in first-out (FIFO), last-in first-out (LIFO), highest SOC first (HSOC), lowest SOC first (LSOC). Moreover, during the charging process, a power reduction curve can be applied to the charging power as the battery reaches higher SOC levels. For example, in the case study presented below, the charging power was set to the charger nominal power until the battery reaches 80 % SOC. Then the power is reduced progressively to reach 50 % of the nominal power when the battery reaches 100 % SOC. All of the models and parameters described can easily be customised.

## III. Case study

Singapore is a tropical island city-state with a land area of 720 $km^2$ and a population of 5.6 million, ranked as one of the most densely populated countries in the world after Macau and Monaco. Due to limited area availability, current government policies favour usage of public transport over private car ownership. The public transport system of Singapore is highly developed and very dense, with more than 5400 buses plying over 580 bus routes, and a daily ridership of 3.9 million. In 2017, the Land Transport Authority (LTA) initiated the electrification of Singapore's bus fleet with the procurement of 50 hybrid buses and 60 electric buses to be delivered by 2020.

### A. Data Collection

Simulating this city-scale bus network required gathering and processing various data sets from different sources. The road network data for Singapore used by previous studies with CityMoS was also used in this study. The list of bus lines and the sequence of bus stops that each line visits were obtained from the LTA DataMall [14]. The bus capacity of the termini was inferred from analysis of the data set used in our previous study [15]. Information about the location and bus capacity of 15 bus depots and parks in Singapore was manually gathered from various online sources. Since detailed daily bus trip scheduling data is not publicly available (this data is kept internally to bus operators), the headway interval between two consecutive buses as published by LTA was used instead to schedule bus departures. The headway value changes depending on the time of the day, with shorter intervals usually during morning and evening peak hours resulting in more frequent bus departures during these time intervals.

### B. Parameters

The results presented in this paper are based on a simulation of all trunk and feeder bus lines of Singapore (586 bus routes), over 5 days of operation. The scenario selected for the following results models a level of electrification of the bus fleet of 100 % and a total fleet of 5526 buses. 70 % of the fleet is modelled as single-decker (SD) buses, the remaining 30 % as double-decker (DD) buses. The parameters for the bus vehicle models are summarised in Table I. The battery specific energy was assumed to be 140 Wh/kg at pack level [16]. In this first version of the model, and given that our case study is situated in subtropical climates where the ambient temperature shows little variation, the HVAC power was assumed to be constant. The nominal power of all charging points was set at 450 kW. This corresponds to a typical value for fast-charging via roof-mounted pantograph. At the end of a charging process, it was assumed that the charging point was unavailable for a minimum of 2 minutes to model the time needed for the preceding bus to clear the area of the charger and the next bus to take its place. The number of charging stations distributed in the termini and depots was derived heuristically using a 2-stage approach. A first simulation is performed with a very high number of chargers such that there is always an available charger at each charging station. The results of this simulation are analysed and, for each charger, we count the number of time steps during which the charger has been in use (this includes the time steps during the night). Then all chargers that were used less than 10 % of the time are removed for the second simulation.

TABLE I
Vehicle parameters

| Parameter | Vehicle type | | Unit |
|---|---|---|---|
| | SD | DD | |
| Mass (excluding battery) | 13.5 | 18.5 | t |
| Front area | 8.3 | 10.35 | $m^2$ |
| Drag coefficient | 0.7 | 0.7 | - |
| Rolling resistance | 0.008 | 0.008 | - |
| HVAC electrical power | 7.5 | 10 | kW |
| Battery capacity | 200 | 250 | kWh |

## IV. Results

This simple case study aims at demonstrating the type of results that can be derived from using a large-scale microscopic model of electric public bus operation and charging. In this section, a selection of the main results are presented. These results are not considered final, yet they already deliver interesting insights into the requirements for electrifying the public bus fleet of a megacity.

### A. General statistics about the bus trips

There were 52,763 service trips and 23,405 off-service trips per day on average, for a daily mileage of 1,309,511 km in total, of which 982,441 km (75 %) were for service trips and 327,070 km (25 %) for off-service trips. The median distance per trip was 18.1 km with a median absolute deviation (MAD) of 10.5 km. For service trips, the median daily mileage per bus was 191 km with a MAD of 47 km, while the median off-service daily mileage was 59 km with a MAD of 30 km. The high variance of the values is a consequence of the high variety of bus services as discussed previously in [15].

### B. Energy demand

The average daily energy demand for the entire fleet in this case-study was 2.20 GWh, of which 1.91 GWh (87 %) were used for service trips and 0.29 GWh (13 %) for off-service trips. This represents 1.9 kWh/km on average for service trips and 0.9 kWh/km for off-service trips (including all vehicle types).

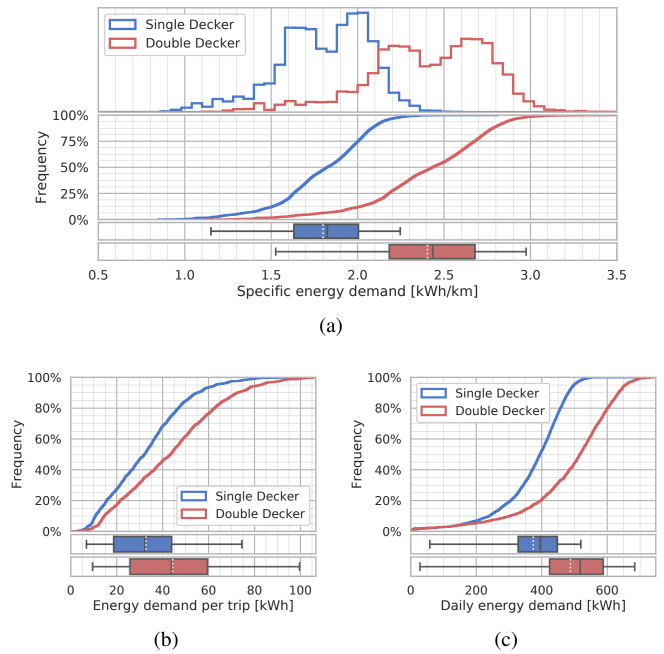



Fig. 2. Cumulative distributions of (a) the specific energy demand (with normalised distributions on top), (b) the energy demand per trip and (c) the daily energy demand per bus for service trips. (Box plot whiskers set at 2nd and 98th percentiles.)

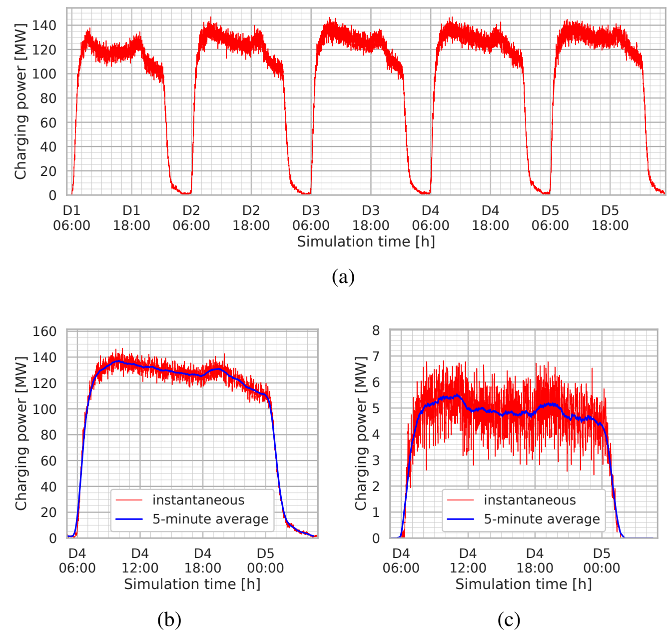



Fig. 3. Charging power curve (a) aggregated over all charging stations for a simulation of 5 consecutive days of operation, (b) aggregated over all charging stations for day 4 and (c) for a charging station at a major bus interchange for day 4.

Fig. 2 provides details about the energy demand statistics and distribution per vehicle type for service trips. Fig. 2a shows the distribution of the specific energy demand for service trips for each type of bus. For SD buses the specific energy demand ranges from 1.1 kWh/km to 2.3 kWh/km with a median of 1.8 kWh/km, while for DD buses it ranges from 1.4 kWh/km to 3.0 kWh/km with a median of 2.4 kWh/km. Taking into account the chosen parameters for this case study, these values are consistent with the expected energy demand values from previous research and existing literature [5], [11], [17], [18].

Fig. 2b shows the cumulative distribution of the energy demand per service trip for each vehicle type. The median value is 32.2 kWh for SD buses, and 43.8 kWh for DD buses, but the dispersion is wide with a MAD of 18.6 kWh and 25.1 kWh respectively. 80 % of the trips require less than 47 kWh for SD and 63 kWh for DD.

The cumulative distribution of the daily energy demand per bus is shown in Fig. 2c. The median lies at 338 kWh for SD and 452 kWh for DD. 80 % of the buses have a daily energy demand of more than 300 kWh for SD and 400 kWh for DD.

### C. Charging Power

For this case study, the HSOC (highest SOC first) selection algorithm was used for selecting which bus to pick from the waiting queue, as well as for deciding which bus to select for a trip departure. The rationale behind this algorithm was described in [4]: choosing the bus with the highest SOC means that the charging duration will be the shortest and the charging point will be made available sooner for the benefit of another bus in the waiting queue. In essence, it attempts to maximise the number of buses exiting the charging station over a given period.

Fig. 3a shows the charging power curve aggregated over all charging stations over the 5 days of the simulation and Fig. 3b shows the same in more details for the fourth day of the simulation. After the first day where the simulation is warming-up, the charging power pattern repeats similarly every day, validating the soundness of the model over multiple days. From 7:00 a.m. to 12:15 a.m, the aggregated charging power stays between 100 MW and 145 MW. Short-term fluctuations of the instantaneous charging power with a magnitude of about 20 MW in a few seconds are visible. This is due to the random arrival of buses in charging stations and the random time at which charging ends among all charging stations. The peak power is reached around 10 a.m. with 147 MW and corresponds with the increased frequency of arrival of the buses that were dispatched during the morning peak hour (from 6:30 a.m. to 8:30 a.m). Similarly, a second peak can be seen between 6:30 p.m. and 8:00 p.m., corresponding to the arrival of buses dispatched during the evening peak hour (from 5:30 p.m. to 7:30 p.m.).

Fig. 3c shows the charging power curve for day 4 for a charging station located at a major bus interchange. It can be noted that the magnitude of the fluctuations relatively to the average power are much higher than when looking at the aggregated power over all charging stations. The magnitude of the fluctuations for this particular charging station are in the order of a few megawatts. They happen when multiple buses arrive or depart the charging station in a short period of time.

## V. Future work

The model described in this paper is under active development. Many different aspects towards validating and improving the accuracy of the model are planned in future work.

Improvements to the traffic and bus dispatching model: (i) An improved model of dwelling time at bus stops based on passenger demand statistics from historical data will replace the current simplified model which assumes a constant dwelling time at each bus stop. (ii) Car traffic and traffic lights at intersections were deactivated while implementing the first version of the bus model in CityMoS as calibrating microscopic traffic models to scales as large as a megacity is challenging. In future works, these will be reactivated which will lead to more realistic trip duration with a lower average speed per trip. (iii) Improvements to the bus dispatching algorithms are planned in order to make it more realistic: instead of dispatching buses from or to depots reactively when termini are getting empty or too full, a proactive algorithm would take into account the planned departures and the buses arriving soon.

Improvements related to the energy demand and charging model: (i) Consideration of variable mass based on passenger count. (ii) Implementation of more detailed battery models to include the effects of battery ageing and better model the battery weight for different battery types. (iii) Stationary battery storage in charging stations to act as a buffer and to reduce the fluctuations of the charging power drawn from the electrical grid will be investigated. (iv) Addition of more advanced charging scheduling strategies to better decide when and where the bus shall recharge. (v) Implementation of more detailed HVAC models to take the solar irradiation and the passenger count in the bus into account.

The flexibility provided by this new simulation model will facilitate future studies at city-scale including but not limited to: (i) Study of different levels of electrification of the bus fleet with their respective charging infrastructure requirements. (ii) Comparison of the impact of choosing different charging power on the required bus fleet and charging infrastructure to fulfil the same operational requirements. (iii) Determining the appropriate battery size for buses while taking into account the highly different energy demand characteristics between different bus routes. (iv) Comparison of different charging strategies. (v) Simulation-driven determination of the location and required number of chargers.

## VI. Conclusion

In this work, we introduced a new agent-based, large-scale microscopic model of electric public bus operation and charging. The operation of buses is modelled in a very detailed manner aiming at reproducing real-world considerations. The modular nature of the agent and behaviour models provide flexibility for the user to customise and improve each aspect of the model to the desired level of detail. Being based on a high-performance traffic simulation platform, the model scales to very large scenarios and enable to study various electrification scenarios considering the entire bus network and infrastructure. The case study for Singapore's entire bus network demonstrates the ability of the model to be applied on large-scale real-world studies for fleets of several thousand buses.

## Acknowledgment

This work was financially supported by the Singapore National Research Foundation under its Campus for Research Excellence And Technological Enterprise (CREATE) programme.

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