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Master's Thesis

City-scale, Agent-based Modelling & Analysis of an Electric Public Bus Transport System

Case Study: Singapore

written by

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Thesis submitted to the Institute for Renewable and Sustainable Energy Systems at the Technische Universität München
In cooperation with TUMCREATE Ltd., Singapore

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Submitted on December 8, 2018

Appendix I

Declaration

I hereby declare that the thesis submitted is my own unaided work and that I didn't use any but the quoted sources.

December 8, 2018

AMINE GOUIAA	Date

Abstract

In a context of global efforts to reduce dependence on fossil fuels, battery electric buses for public transport are a promising solution to decrease cities carbon footprint. Supported by the progress of energy storage and of ultra-fast charging technologies, full electrification of public buses fleet has become nowadays feasible and realistic. However, an optimised system is essential to ensure an economically viable transition, while maintaining high service reliability. Worldwide, transport agencies are testing electrified bus lines while some mega-cities have already succeeded their full transition. This master thesis report describes the modelling of an agent-based, city-scale public bus transport system implemented in partnership with TUMCREATE Ltd. The developed simulation enables analysing the electrification, then the operation of a public bus fleet, including charging stations, termini, and depots. With 98 % of bus routes under 45 km, and 2 hours driving time, the city-state Singapore seems an ideal place to study large-scale bus networks electrification. The models were calibrated and validated using a historical real-world dataset, covering the entire bus fleet of this south-east Asian island. More than 25,000 buses journeys, operated by 5700 buses on 355 bus routes were simulated. The results show that a full electrification of the current public bus fleet in Singapore would require around 350 chargers and induces a daily charging power demand reaching 120 MW during peak hours.

Kurzzusammenfassung

Im Zusammenhang mit den globalen Bemühungen, die Abhängigkeit von fossilen Brennstoffen zu verringern, sind batterieelektrische Busse für den öffentlichen Verkehr ein vielversprechender Weg, um den CO_2-Fußabdruck der Städte zu verringern. Ein optimiertes System ist jedoch unerlässlich, um einen wirtschaftlichen Übergang unter Beibehaltung einer hohen Servicezuverlässigkeit zu gewährleisten. Dieser Master-Thesis-Bericht beschreibt eine agentenbasierte Stadtverkehrssimulation in Zusammenarbeit mit TUMCREATE Ltd. Die entwickelten Modelle ermöglichen die Anzeige und Analyse der Elektrifizierung, dann den Betrieb einer öffentlichen Busflotte, einschließlich Ladestationen, Terminals und Depots. Mit 98 % der Busrouten unter 45 km, und 2 Stunden Fahrzeit, scheint der Stadtstaat Singapur ein idealer Ort zu sein, um Busnetz-Elektrifizierung. Das Modell wurde kalibriert und validiert unter Verwendung eines historischen realen Daten-Sets, das die gesamte Busflotte der südostasiatischen Insel abdeckt. Simuliert wurden mehr als 25,000 Busse täglich, einschließlich 355 Buslinien und mehr als 5000 Busse. Die Ergebnisse zeigen, dass die Elektrifizierung der gesamten öffentlichen Busflotte in Singapur 350 Ladegeräte benötigt, die über alle Ladestationen verteilt sind, was zu einer 120 MW täglichen maximalen schwankenden Ladeleistungsnachfrage führt.

Master Thesis

Title

City-scale, agent-based modelling and analysis of an electric public bus transport system – Case study: Singapore

Applicant
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Supervisor
Marc Gallet

Description

Goal:

The master thesis's main goals are to:

- improve the modelling of the operation for electric buses in the agent-based simulation framework CityMoS,
- validate the implementation,
- analyse the data output of the simulation and compare the results for a chosen variation of input parameters.

The operation of electric buses will be implemented through models for vehicles, termini and depots interacting with each other through decisions algorithms. The algorithms decide for example:

- how to prioritize buses competing for a limited number of chargers at charging stations (charging strategies),
- when and which buses to dispatch between charging stations and depots through dead-heading trips,
- which buses to select for a given service trip.

Tasks:

1. Review existing literature on electric bus operation and research the characteristics of current electric buses on the market.
2. Based on a small case study, improve the design and implementation of bus operation in the existing-agent based simulation, with particular focus to the dispatching and recharging strategies.
3. Implement data output for further validation and analysis of the simulation results.
4. Validate the implemented models and overall bus operation on a city-scale case study for the entire bus network and fleet of Singapore.
5. Analyse the results of the simulation for a reference scenario and then for a variation of the major input parameters (electrification level, nominal charging power, charging strategies, etc.).

Contents

1 Introduction

1.1 Context

20 years after the United Nations Climate Convention succeeded in introducing global warming to the world environmental diplomacy agenda, almost 200 countries took vows to engage in a more resourceful fight against greenhouse gas (GHG) emissions [1, 2].

Meanwhile, the World Health Organization (WHO) has been pointing out the transport sector as a significant and growing contributor to the discharge of fine particles in the air. Land transport is accountable for 16.5 % of total CO_2 emissions, with a 3.3 % annual average increase between 2001 and 2015 [3, 4]. Buses are on the sight line of this coordinated action, as commuters are particularly exposed to gases and heat emissions at bus stops [5, 6].

At the same time, land scarcity and urban demographic growth have become serious challenges for governments worldwide. Urban population is expected to increase by another 2.5 billion by 2050 [7]. Thus, high investment funds are required for the extension of transportation networks. Under budget pressure, this represent the main slowing factor to the improvement of public transport service quality.

Under this demographic and socio-environmental pressure, the global consensus on the situation urgency led to remarkable progress in electric power train efficiency. It resulted in the further development of alternative fuel public transport buses such as fuel cell electric buses, battery electric buses, and hybrid electric buses [8].

The advantages of electrifying conventional diesel-powered buses specifically are numerous. It improves Well to Wheel (WTW) efficiency, lowers energy consumption per vehicle-kilometre and decreases local polluting emissions [9–12]. As a result, a shift to electric powertrains reduces foreign energy imports and increases independence from gasoline prices [13]. Also, it enables a better road usage [14], as well as adding ride comfort perceived by passengers (e.g. noise, smell, vibrations) [15]. Finally, electric powertrains require less maintenance and ensure high reliability [10].

Worldwide, new prototypes are being operated and trials of electrified lines are showing the way forward such as in Europe [16–19], North-America [19–21], China [4, 22], Singapore [14, 23], Malaysia [10], to mention only some of them.

Figure 1.1 shows the predicted market shares growth of alternative energies buses (compressed natural gas (CNG), liquefied petroleum gas (LGN), hybrid, and electric buses) in different regions of the world by 2020. By 2020, the number of electric buses will reach 15 % of all buses. More optimistic, Chediak [24] forecasts that electric buses would represent 50 % of the world buses fleet by 2025.

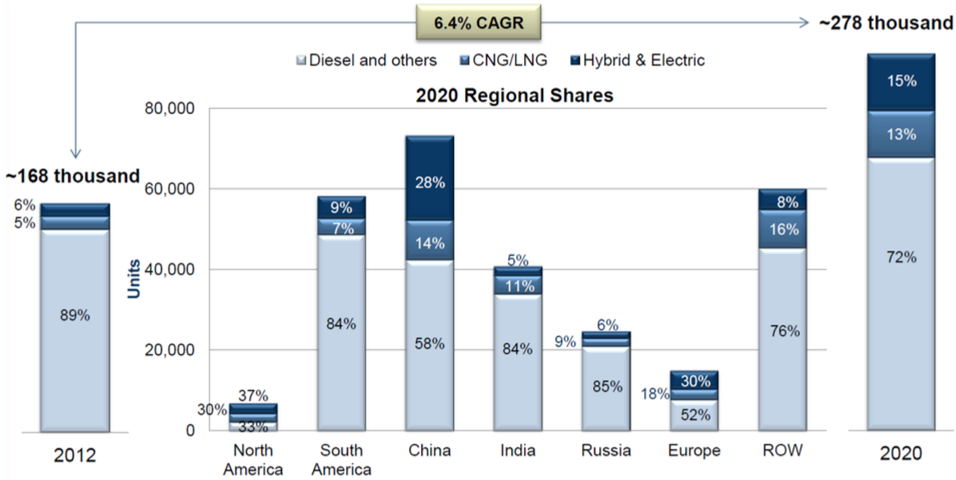


Figure 1.1: 2020 market shares prognosis of alternative energies buses worldwide (stand 2012) [25].

1.2 Motivation

Despite the political engagement and the advantages of electric buses, some aspects are still limiting these technologies wide introduction and their implementation on a large scale [26]. Until now, most of the on-field trials and studies are limited to one or few battery electric buses (BEBs) and bus lines. However, the complexity of big cities networks exceeds the simple addition of single bus lines. Thus, every transport system has to be considered as a whole.

The electrification of a conventional buses fleet by a one-by-one replacement is indeed hard to reach, as large batteries ensuring the same energy capacity increase the bus weight significantly [27]. Electric buses have 70 % to 90 % availability in comparison with conventional diesel-fuelled ones [8, 22]. Thus, 1.1 to 1.4 BEBs are needed to replace one diesel-fuelled bus. Therefore, accurate dimensioning and optimal planning are crucial and critical for the viability of the system. Investing on a trial and error basis is expensive [5, 16, 28, 29]. Also, the involved electricity profile and the achieved system efficiency are determining how ecological this transition can be [4, 8, 18].

Studying the various operational characteristics of an electric bus network such as queuing, charging, and dispatching is an important step towards a wider deployment of BEBs. City-scale analysis of buses range, energy consumption, grid adaptability, total cost of ownership (TCO), and environmental impact are crucial to reduce risks while addressing reluctances of decision-making authorities (e.g. “Guinea pig syndrome”, technology and range anxiety, economical viability) [10, 26].

1.3 Project Overview

This master thesis report describes the work achieved on modelling, validating and analysing a city-scale agent-based electric public bus transport system. The focus was set on the charging process and infrastructure. Through this work, an analysis of the daily energy consumption of a mixed bus fleet in Singapore, of its daily charging power demand, and of the required charging infrastructure was possible.

It complements published work by Gallet et al. [14] and supports works on large scale electrification of public bus fleets [10, 12, 30]. This work was accomplished with TUMCREATE Ltd and represents the result of a cooperation between Electrification Suite and Test Lab (ESTL) and Area-Interlinking Design Analysis (AIDA) teams.

Timeline

Table 1.1 gives an overview of the temporal framework of this work and summarises the milestones achieved during this master thesis:

Table 1.1: Timetable of achieved milestones in the current work.

Date	Milestones reached
04-06-2018	Start master thesis
18-06-2018	Complete market research on electric buses
17-07-2018	Extend University Town bus network model to 5 lines
21-07-2018	Unify models data structures
25-07-2018	Consolidate termini, depots, and electric buses models
31-07-2018	Enable planning trips in advance and booking buses at termini
13-08-2018	Implement charging, dispatching, and balancing strategies
28-08-2018	Fix map deadlocks and extend charging station models
05-09-2018	Set data output and start validation phase
03-10-2018	Start simulating with LTA time schedule
19-10-2018	Write paper draft on modelling a city-scale electric bus network

1.4 Thesis Structure

The rest of the report is structured as follows.

Chapter 2 introduces background knowledge about electric powertrains, charging operations and infrastructure requirements.

Chapter 3 gives an overview of the state-of-the-art on buses electrification. The scientific literature related to the topic is grouped and reviewed. Finally, results of the realised market research on electric buses are presented.

Chapter 4 presents the current case study: the city-state Singapore. Main specificities of the location are shown and the motivation behind choosing it as a case study is explained. Data used for this model is presented and assessed.

Chapter 5 describes the followed methodology to implement, to calibrate, to validate the different models, and finally to process the simulation output.

In Chapter 6, results obtained after processing the output of the simulated scenarios are interpreted. Plotted data is exhibited, analysed and discussed. This chapter is concluded by the assumptions and limitations made during this work.

Finally, Chapter 7 summarises this work. Outlook on future works concludes this report.

A diagram of all sections interconnections from this work is presented in Figure 1.2. The coloured arrows represent the different parallel dependencies: electric buses models (blue), charging infrastructure models (red), and data input to data output pipeline (green).

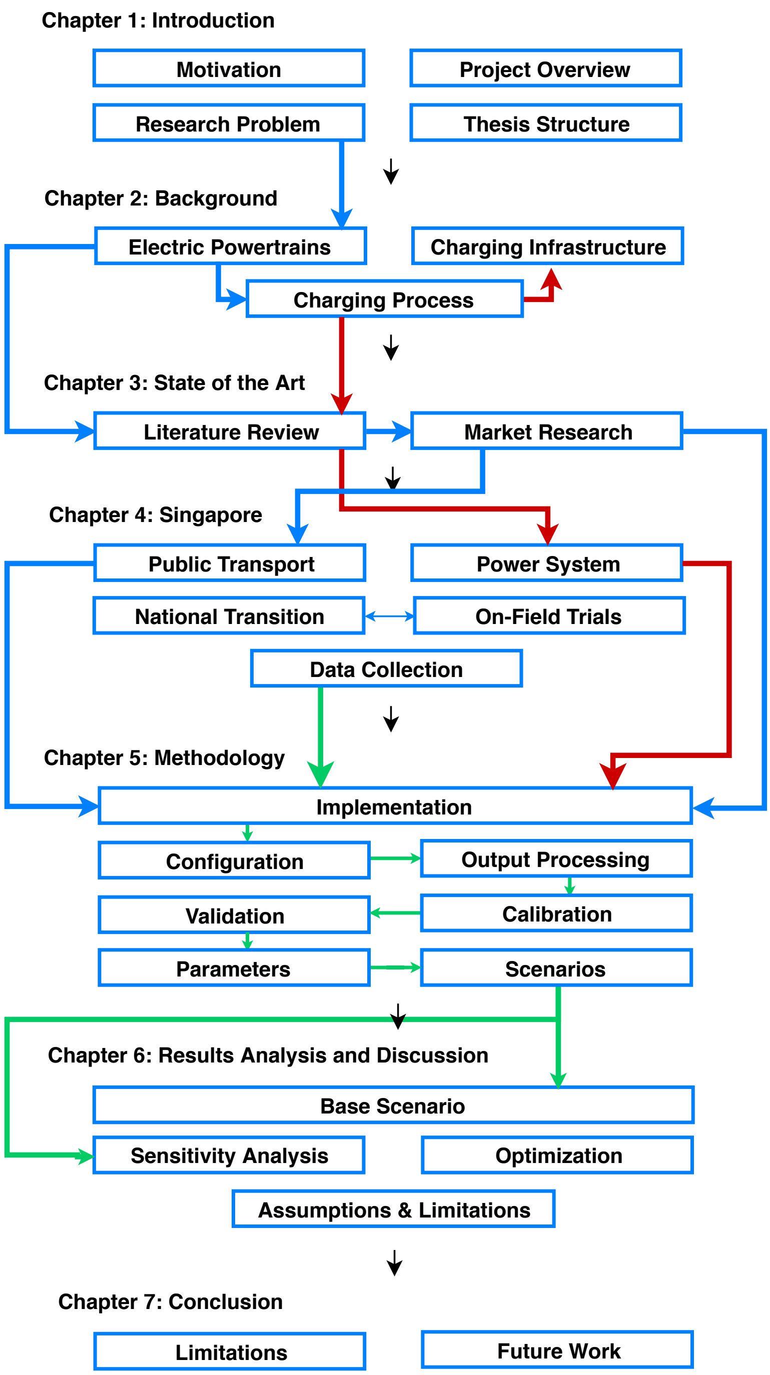


Figure 1.2: Overview of the report structure.

2 Background

2.1 Electric Buses Powertrains

Alternative powertrains to conventional combustion motors are characterised by different levels of electrification or hybridisation, according to their propulsion system architecture. They can be classified in three categories [8]: battery electric bus (BEB), fuel cell electric bus (FCEB), and hybrid electric bus (HEB), or plug-in hybrid electric bus (PHEB). The difference between the various technologies is mainly the power source for the engine. With the exception of (plug-in) hybrid parallel electric buses that combines both electric and combustion motors, all alternative bus types derive their movement energy from an electric machine.

A reliable electric bus should show a certain number of characteristics according to [20]:

- stores the right amount of energy needed for service operations,
- can be operated safely,
- is compact and light weighted,
- can be charged as often and quickly as necessary, with minimum battery degradation,
- is available at cheap price.

2.1.1 Battery Electric Bus (BEB)

Battery electric buses (pure electric) are buses propelled by the energy stored in an on-board battery package, composed of multiple cells, usually of Lithium-ion polymers type. The engine architecture does not include any combustion process. An overview of a BEB powertrain architecture is represented in Figure 2.1. BEB batteries capacity varies according to the operating mode of the bus from 12 kWh to 650 kWh.

Electric buses can be operated like trolleys, connected permanently to a pantograph or at intervals to gain charging boost every few minutes. More frequently, BEBs drive for a period of time, until the battery reaches a certain limit and needs to recharge. The charging process is then done via a wire, or a wireless charger. More on the charging technologies, procedures and operations of electric buses can be found in Section 2.2.

The battery of an electric bus is very critical to its operations, as it represents the only source of energy to propel the vehicle, in contrast to hybrid and fuel cell electric buses. The battery represents also one of the heaviest components of a bus, which make its sizing very important. In addition, energy storage technologies have not reached full maturity yet. For this reason high capacity batteries needed for pure electric buses are still the most expensive component.

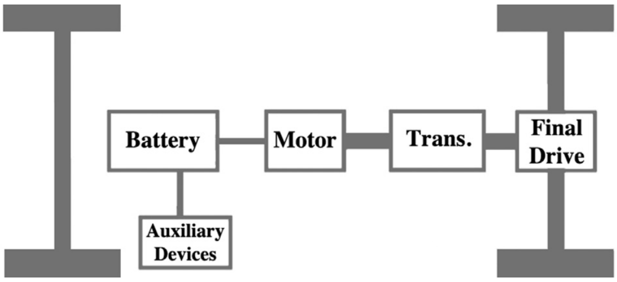


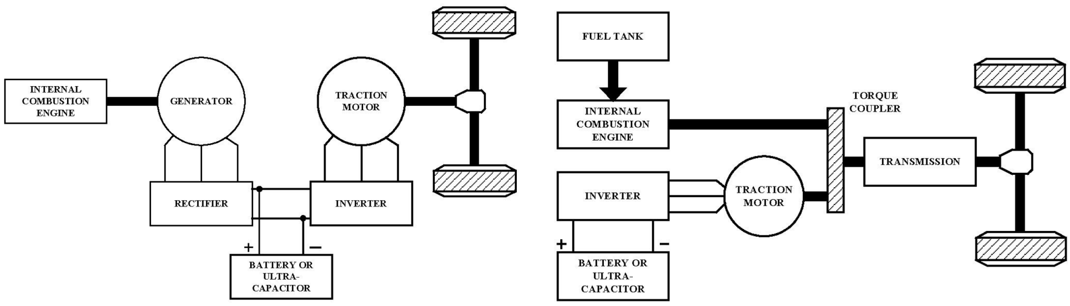
Figure 2.1: Diagram representing main blocks of BEB powertrain [8].

2.1.2 Hybrid Electric Bus (HEB)

Hybrid Electric buses are equipped with both an electric motor (EM) and an internal combustion engine (ICE). ICEs can be fuelled with diesel, gasoline, natural gas or biodiesel. Alternatively, the battery can be charged directly from an external electric source, to give more flexibility to the whole system, giving its name to the PHEB.

Two main powertrain architectures are possible for hybrid electric buses, depending on how the EM and the ICE are set:

- Series Hybrid Electric buses use the ICE to generate electric power driving the electric motor. In case of over-generation, the energy is redirected to recharge the battery [31]. A representative image is shown in Figure 2.2(a).
- Parallel Hybrid Electric buses enable both combustion and electric motors to propel the vehicle at the same time. It is equipped with a direct mechanical connection between ICE and the wheels, mostly used for highway drive and an EM to accelerate [31]. An image of the powertrain architecture is shown in Figure 2.2(b).



(a) Series hybrid electric (b) Parallel hybrid electric

Figure 2.2: Diagrams representing main components of hybrid powertrains [31]

Although this technology shows a great level of flexibility, the complexity of its powertrain is increased due to the two-folded architecture. Under favourable conditions, a full transition to pure electric can be more interesting than a partial hybridisation from an environmental point of view.

2.1.3 Fuel Cell Electric Bus (FCEB)

Fuel cells technology is based on the reaction between hydrogen and oxygen. The cells are filled with hydrogen during the tanking process. In contrast to ICE, driving energy is not derived from a combustion process but through an electrochemical reaction between hydrogen fuel with oxygen or another oxidizing agent [8]. The reaction between the components allows ions to migrate inside the electrolyte and to generate electrical energy to be delivered to the EM for movement, as long as the chemical actors are still available in the cell and are not fully consumed. It is also possible to couple this technology with an electric battery to gain more reach, analogous to hybrid powertrains.

The energy efficiency of a fuel cell varies between 40 % to 60 %. However, critics claim that this technology is not viable due to the inefficiency of producing, transporting, and storing chemical components needed. Also, price of electricity generated by fuel cells is calculated to be 4 times as expensive as electricity drawn from the electrical transmission grid [32]. Finally, flammability of hydrogen represents a safety concern to the users of this technology.

2.2 Charging Infrastructure

Analogous to gas stations for conventional diesel-fuelled buses, charging stations enable electric buses to recharge their batteries and so, to increase their driving range. Due to the tight public buses schedules, infrastructure must be planned so that electric buses are able to operate as long as possible during the day, ensuring the highest availability.

In contrast to electric vehicles (EVs), one of the advantages of electrifying public buses is the availability of assigned operative structures for buses maintenance and parking, where chargers can be installed and scheduled accordingly. In addition to dispatch timetables, an optimised charging schedule is predictable and partially deterministic (taking traffic disparateness into account). At termini, depots, bus stops, or on-route, charging stations can be situated at different locations. Various technologies are available and can be combined to optimise the electric buses operations.

2.2.1 Wired Charging

Wired (conductive) charging is characterised by a physical contact between the battery and the charger. This is currently the most frequent technology used for EVs and BEBs. Wired chargers are found in charging stations at transit facilities such as parking places, bus stops, termini and depots. A person is needed to plug the charger to the bus.

2.2.2 Pantograph Charging

A pantograph is a fixed or mobile arm and infrastructure installed to enable a physical contact between an electric bus battery and a charger [20], analogous to the wired charging. Additionally, it avoids faulty plugging by automatising the docking process. Thus, this technology maximises the ratio of stopping to charging time and ensures a higher buses availability.

In the case of a fixed pantograph, a bus driver needs to place the bus at the right position to enable the charging procedure. In contrast, a mobile arm pantograph reaches the electric bus automatically with included detection features such as laser technology, even if the bus is not perfectly positioned.

Figure 2.3: Charging electric bus via an overhead pantograph [33]

2.2.3 Wireless Charging

In opposition to wired or pantograph technologies, wireless charging delivers electric energy to the BEB without physical connection between the electricity source and the battery. To enable this technology two plates are needed. The first receiver plate is placed under the bus. The second emitter plate is usually installed on ground level or buried. When the second plate detects the presence of a receiver plate (BEB) according to communication protocols, it starts emitting energy. These electromagnetic waves will be captured by the bus, will be reconverted to electricity and will charge the battery.

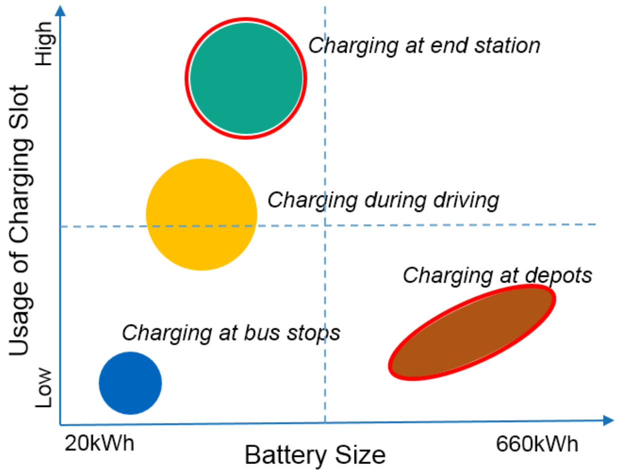
Some charging systems are designed analogous to pantographs in a way that energy transferring plates move toward each other to increase charging efficiency. This is used when the bus is parked, or charging at transit operative locations such as depots, termini, and bus stops. In the case of wireless charging on-route, the distance between the two plates is constant.

However, apprehensions are present on the efficiency of the technology, indirectly proportional to the distance between plates and the battery. Rain, snow and ice can increase this distance and so, decrease further the performance, increasing charging and unavailability time. The high costs and the needed infrastructure modifications for the implementation of this technology are still handicapping its wide adoption.

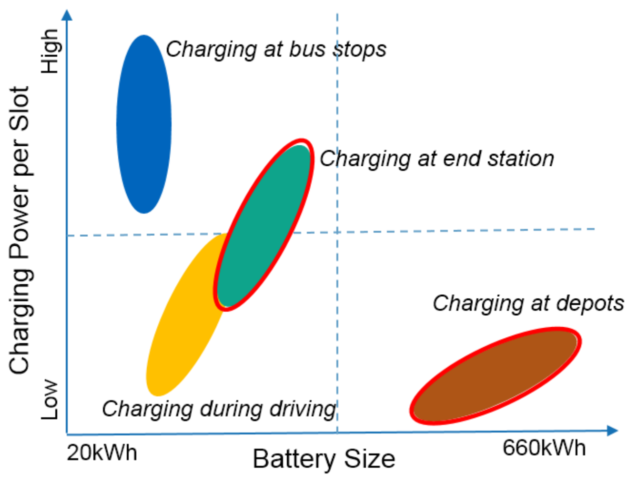
2.3 Charging Process

Electric buses can charge at different operative locations or on-route, at different paces, and with various technologies. The system costs are divided, either added to the electric bus itself (expensive high capacity battery) or to the charging infrastructure (chargers count and more frequent ultra-fast charging). "There is a trade-off between frequent high-power charging of small batteries on one end of the scale and slower charging of much bugger batteries on the other hand." [29].

Given advantages and drawbacks of every charging procedure presented below, a combination of different charging strategies can be the way to move forward with the question. A summary of the charging strategy dilemma is shown in Figure 2.4 and the four main electric buses charging processes are detailed in the following subsections.



(a) Usage of charging slot vs battery size



(b) Chargers power vs battery size

Figure 2.4: Overview of the charging infrastructure and charging strategy dilemmas for electric buses [29]

Göhlich et al. [34] consider in their most recent paper that electric buses can be operated in more than 100,000 configurations, in function of the energy source, refuelling strategy and interface, on-board energy source, powertrain, body type, and heating, ventilation, and aircon (HVAC) technology. An overview of the morphological matrix of available options electric buses systems is shown in Figure A.1.

2.3.1 Depot Charging

Also known as overnight charging, depot charging is the strategy that is the most similar operation of electric buses compared to conventional buses operations. With a similar availability as diesel-fuelled vehicles, pure electric buses are charged during the night for a long period (4 to 8 hours) at low power (inferior to 100 kW), to be fully charged at the start of the next day. Under favourable conditions and with the right sizing, electric buses manage to complete a full dispatch day without the need for any extra charge boosts.

To enable depot charging, a BEB must at least be equipped with a battery capacity usually superior to 250 kWh [29]. Doing so increases substantially the weight of the bus and per se, affects the energy consumption of the bus and the number of passenger allowed [29]. The vehicle costs of purchase are also considerably increased, as battery packs are one of the most expensive components of electric vehicles.

Assuming slow charging technology used, this charging method is possible if every parked bus in depots is assigned one charger overnight, resulting in the need for a high number of chargers installed. Alternatively, buses would need to be driven to the chargers during the night to enable charging multiple buses with only one charger. Although electric grid friendly, depot charging decreases the usage of the charging infrastructure, because it is almost not used during the day. In case its battery is depleted or reaches critical values, a bus needs to be sent back to depot and must be substituted by another vehicle, as charging cycles take several hours.

2.3.2 End Station Charging

Allowing more charging opportunities, end-station charging is done at end-stations (destination termini). Terminus charging is also labelled as opportunity charging in [35] or as boost / proactive in [11]. In [5], opportunity charging is including charging on-route at bus stops.

This charging method gives charging opportunities to BEBs every time they finish a terminus-to-terminus journey. As most services have a certain time buffer between consecutive dispatching (from 10 min to 30 min in Singapore), this time is used by the buses to gain a charge boost until reaching the next terminus.

Adopting this charging strategy enables downsizing the battery capacity to values ranging around 250 kWh to 100 kWh. In contrast to depot charging, this strategy increases the charging infrastructure usage. Buses availability is also augmented during the day by decreasing charging time, as it enables sharing the usage of slots for many buses over the day. Nominal power per charger is usually between 150 kW to 600 kW [29, 36].

However, the bus must have enough energy to complete multiple journeys without charging. Also an additional safety buffer must be planed, as chargers could be all busy when a bus reaches a terminus and a new journey is scheduled and has to be driven. Furthemore, queuing strategies are necessary to ensure an optimal charging procedure. Finally, increasing charging power has an impact on the battery lifetime [37].

2.3.3 Bus Stop Charging

Charging at bus stops enables buses to gain an energy boost while passengers are boarding and alighting. The battery size is proportional to the distance between bus stops (in average 588 m in Singapore). The shorter the distance between two bus stops (and so between two chargers), the smaller the battery can be. Considered batteries have a capacity from 80 kWh to 40 kWh. However, it can not be infinitely downsized proportionally to short bus stop to bus stop distance. Buses batteries must be able to stand frequent charging at high power and also, to miss charging halts in case that chargers are busy or out of service.

This strategy implies installing ultra-fast chargers at all or specific bus stops along the bus network. Energy storage technologies (stationary batteries) are often included in the architecture of the charging station at bus stops to reduce costs of the grid connection. This represents a trade-off to reduce grid connection costs against the additional costs of the energy storage system. Thus, charging of the stationary batteries is done at low power, while a high power buses charging is enabled [29]. Also, some researchers proposed to install chargers at bus stops or interchanges next to railway stations, where access to higher voltage transport grid is possible in order to minimise infrastructure costs [38].

Considering the different traffic conditions and the auxiliary energy consumption source on board, advantages of this charging method in comparison to terminus charging are limited. This charging strategy enables an independent operation of the BEB from the route length and, with favourable conditions, battery capacity can be smaller. However, dwelling time varies from few seconds to one or two minutes per station. Even with the highest charging power, the energy transferred during dwelling is limited. Increasing dwelling time is hardly acceptable as commuters would wait longer to reach their destinations and the whole network schedule would have to be altered.

2.3.4 On-Route Charging

With overhead wires or inductive charging, buses are able to charge their batteries while driving. This technology decouples the charging time from the dwelling process and so, enables increasing battery energy while driving towards the next destination.

Advantage of this strategy is merging completely the charging with the driving time and so, decreasing the buses unavailability. However, this method is based on major changes in the city infrastructure and can be too expensive. Kilometres of roads per bus route must be modified to ensure long enough charging periods.

Also, the size of the battery is proportional to the distance between two charging roads, which is different from one bus route to another, making the whole planning process more complex. Finally, buses are only charging for a few seconds on the same road, and so, usage level of charging infrastructure stays low over the day. For the case of inductive charging, efficiency of the energy transfer is proportional to the distance between the receiver and the emitter. For all these reasons, this charging strategy may result in a poor general performance.

3 State-of-the-Art

3.1 Literature Review

Economical, environmental, operational, and energetic aspects of public bus fleet electrification were studied through developed models in various regions of the world. Most of this research follows a similar methodology, based on three main stages.

First, bus lines and network specificities are evaluated. Then, energy demand is considered. With the collected data on consumption, charging infrastructure and strategy are modelled and scenario feasibility is analysed. Finally, the constraints on an electric bus network are formulated mathematically and calculations of optimised parameters such as charging infrastructure, chargers nominal power, and bus fleet electrification level are made.

The most relevant and recent studies are presented below, grouped according to the three methodology steps introduced previously.

3.1.1 Energy Consumption Models

Since diesel fuel has about 100 times the energy density of a lithium-ion battery, statistics on combustion motors were never of great interest from a scheduling point of view. On the contrary, operating an electric bus network is impossible without considerations of bus routes energy demand. Some researchers focused on calculating the bus energy needs, by modelling the real-world buses driving and consumption behaviours in simulation environment.

Kontou and Miles [39] analysed the Milton Keynes' pilot project implemented in the United Kingdom [5]. Impact of traffic conditions and temperature was proven to be important on both energy and GHG emissions.

Vepsäläinen et al. [40] searched for relevant route characteristics impacting BEBs consumption in Finland, based on Genikomsakis and Mitrentsis [41] work. Bus stops distribution, routes characteristics, traffic level and driving behaviour were identified as having the most impact on energy consumption. The authors confirm also that "an electric city bus can have a broad range of possible energy consumption rates due to mission condition variations" and "the range of possible mission profiles should be determined during the concept phase of designing a city bus".

Perrotta et al. [42] simulated the consumption of an electric bus on different public transport routes in Oporto, Portugal. They identified a correlation between the energy consumption and the distance separating bus stop. They also highlighted the fact that proofs of public buses fleet electrification feasibility were still missing for a complete network scale. The same gap in the state-of-the-art literature was also addressed by Mohamed et al. in their recent article [26], arguing that "the cumulative impacts of electric bus operation in varied sequential routes require a detailed investigation".

Gao et al. [11] calculated in their work the energy consumption of the bus network in Knoxville, USA. It was done based on a longitudinal dynamics model of diesel buses. They noted that battery size must be adapted to the bus route and implementing different sized batteries should allow a greater operation flexibility and enable lower investment costs.

Gallet et al. [14] proposed a alternative approach to calculate buses energy consumption from departures and arrivals time steps, applied to the city-state Singapore. This method is based on a simplified longitudinal dynamics model and is designed to be applicable on a city-scale using only commonly available bus network data.

3.1.2 Electric Buses Operations Models

A second group of scholars studied the different aspects of operating electric buses. Given the wide operation possibilities and the different implementation dilemmas, as mentioned in Section 2, aim of these works is to model, combine and compare the multiple charging infrastructures and strategies.

Teoh et al. [10] developed a model to compare five different scenarios of public buses electrification in Putrajaya, Malaysia (16 bus lines, 360 km, 170 buses). Chargers nominal power, bus routes characteristics, passengers and bus stations counts were tuned and required number of electric buses, as well as charging points was calculated. It was concluded that fast-charging technologies are the key to operational feasibility and financial viability. Also, optimised electric buses scenario was proven to outperform conventional operations based on gasoline fuelled buses.

Olsson et al. [29] modelled a public bus electrification environment. Electricity supply, charging system, dwelling and operations cycles were simulated in order to calculate the total costs induced by operating electric bus routes in Sweden (2 bus lines, 10 buses). Overnight charging and opportunity charging at termini were considered and compared with different buses characteristics. Results showed the importance of reducing the battery size. It was concluded that a high buses mileage minimises the overall costs.

Pihlatie et al. [6] presented a TCO calculation tool applied to an electric bus line in Helsinki region, Finland (1 bus line, 9.14 km, 10 buses). Long-range and short-range electric buses operations were simulated, based on opportunity charging at both service line ends. It was concluded that short-range BEBs with smaller batteries (80 kW) are the most promising alternative to conventional diesel-fuelled buses. Long-range pure electric buses (250 kW) only become economically attractive when they show a high mileage and usage level.

Qin et al. [43] researched the impact of varying bus count and minimum charging bus state of charge (SOC) from 20 % to 80 % on the system costs and its total power demand in Tallahassee, USA (1 bus line, 20 km, 4 buses to 12 buses). To charge 72 kWh-battery buses, the authors assume an on-route ultra-fast technology with 500 kW chargers nominal power. The charging model is based on a first-in first-out (FIFO) queuing to charging prioritising strategy. It was concluded that increasing charging frequency by decreasing SOC charging limit result in lower operating costs.

De Filippo et al. [13] were to our knowledge the firsts to develop a simulation model that compares various queuing policies with varying charging powers and to analyse the impact on queuing time and feasibility in Ohio, USA (6 bus lines, 52 km, 22 buses). The proposed charging priority algorithms are: FIFO, highest SOC first (HSOC) and lowest SOC first (LSOC). Results showed that FIFO queuing strategy led to the longest waiting time, in contrast to HSOC, that resulted in the shortest queuing time. To ensure that the bus fleet size constraints are respected, the dispatch timetable had to be modified to allow longer dwelling intervals. The author concluded by highlighting the necessity of an additional complete feasibility study.

Mohamed et al. [35] modelled different operation scenarios of a public electric bus fleet in a Canadian city (9 bus lines, 90 km, 11 buses to 13 buses). The resulting charging power demand and infrastructure requirements, given different charging strategies (flash, end-terminus and overnight), were compared. Three battery capacities (80 kWh to 324 kWh) and four charging power (80 kW to 500 kW) were modelled, and charging priority was given to lowest SoC bus (LSOC). The impact on local distribution grid was assessed. The results showed that although more grid friendly, charging the buses in depots overnight is not a viable solution while on-route charging requires less buses and provides more availability. Finally, the authors confirmed the necessity to study further various combinations of infrastructure and operational aspects.

3.1.3 Optimisation Scenarios

A third category of scientific literature modelled electric bus operation through mathematical optimisation models. These models usually aim at finding the optimal infrastructure and operation schedule to maximise infrastructure usage and to minimise costs. Various optimisation tools such as genetic algorithms (GAs) or mixed integer linear programming (MILP) were used to determine optimal scenarios for their case studies.

Ke et al. [30] developed a model of the bus network in Penghu, Taiwan (15 bus lines, 230 km). The impact of charging strategy and optimised schedules on the electrification cost of the transportation infrastructure was studied. It was concluded that the adoption of day-time opportunity and overnight depot combined charging strategy decreases implementation costs.

Kunith et al. [38] optimised the count and locations of the on-route chargers (at bus stops) to decrease electrification costs while ensuring operational requirements in Berlin, Germany (16 bus lines, 335 km, 1 depot). Different scenarios were simulated, where various battery sizes (90 kWh to 150 kWh), conductive and inductive charging powers (200 kW to 500 kW), weather conditions and dwelling intervals were modelled.

The authors analysed the impact of these parameters on energy consumption under opportunity charging assumption. The results showed that charging power has the biggest impact on the sizing of the electrification infrastructure . It was also shown that auxiliary energy consumed through heating and cooling plays an important role in predicting the energy consumed by transport systems. Finally, the need for further studies on a mixed battery capacity fleet with adapted battery sizes to driven bus routes was noted.

Wang et al. [21] developed an optimisation framework that aims at decreasing electric buses implementation costs, by looking at the best charging infrastructure size, location and scheduling in Davis, USA (15 bus lines, 185 km, 30 buses). This work was one of the first to our knowledge to take into account the dead-heading mileage after Wen et al. [44] work. The sensitivity analysis showed that the annual total costs did not vary with the variation of charging duration, however, it is highly sensitive to battery deterioration.

Rogge et al. [27] focused on cost-optimisation under different dispatching timetable, fleet mix and charging infrastructure in two different bus routes in Aachen, Germany and Roskilde, Denmark (2 bus lines, 34 km, 26 buses). Dead-heading was also studied, reflecting off-service, operational driven distances between depot and starting bus stop.

Off-service driven distance was representing 10 % of total mileage. The author concluded that mixed fleet composed of conventional and electric buses shows costs advantage while choosing 100 % electric fleet ensures more efficiency in depots and workshops. The results show that light-weighted buses are the most energy efficient, although their limited range resulted in increased dead-heading and driver costs.

Finally, Xylia et al. [12] were to our knowledge the first who simulated bus network electrification on a larger scale in Stockholm, Sweden (143 bus lines). Bus routes electrification potential under costs and energy consumption optimisation scenarios were studied. Opportunistic way of charging was chosen, supported by additional 14 recharging points at major public transport hubs.

It was concluded that an optimised mixed fleet results in equal annual costs than a 100 % biodiesel fleet. Also, the higher costs of purchase and charging infrastructure can be balanced by the efficiency of the electric engines and the lower costs of electricity.

3.2 Market Research

In this work, a market research was done to explore the manufactured BEBs parameters. It aims at grouping knowledge on available electric buses and improve the implemented models with real-world parameters. A similar work was done in [45–47].

Table 3.1 shows a partial overview of the collected data. Type column includes single decker (SD), double decker (DD), and articulated bus (AB). Coaches were also included in the market research, with lengths varying from 4 m to 24 m. Passengers capacity data was collected from already manufactured models.

Most manufacturers have flexible designs, that are adapted according to the needs of their clients and the specificities of the tender targeted. A manufactured electric bus technical characteristics and price vary when comparing multiple information sources and for different locations. Battery capacity, charging power, and charging method depend on the combination of features selected to be implemented in the bus model and the final price category aimed for. Product models serve mainly to make manufacturing easier and marketing more efficient.

Table 3.1: Overview of the battery electric buses available on the market and their technical specifications.

Manufacturer	Type	Length [m]	Gross Weight [ton]	Passengers Capacity	Battery Capacity [kWh]	Charging Power [kW]	Motor Power [kW]
ABB	SD	18 - 24	n/a	132	70 - 130	45 - 400 - 600	n/a
ADL	SD	12	18	86	324	80 AC	180
ALSTOM	SD	12	n/a	77	272-346	n/a	180
ANKAI	SD	12	14-18	40-70	300	100	100-200
AVASS	DD	11,3	20	85	310	n/a	185
BLUEBUS	SD	12	20	100	270	n/a	n/a
BOZANKAY	SD	12	18	75-232	200-230	4-100	240
BYD Auto	SD	12	19	68 - 80	380	30 × 2	180
BYD Auto	AB	18	29	150	591	40 × 2 - 200	300
CAETANOBUS	SD	14	20	110	7 - 150	150	160
EBUSCO	SD	12	12	90	311	75-120	220
IRIZAR	SD	10.8-12	20	76-80	282-376	80-100	180
LINKKER	SD	13	16	80	55	350	180
NEW FLYER	SD	12.5	14	83	100-545	300	n/a
OPTARE	SD	9.2-11	11	55	92-138	42 - 60	150
OPTARE	DD	10.5	18	99	200	40	200
PROTERRA	SD	12	20	40 s	94 - 660	163 - 325	380
SKODA	SD	12	19	82	80-230	100-600	160
SOLARIS	SD	12	19	90	240	120-450	160
URSUS	SD	12	18	80	120 - 150	30 - 200	170
VDL	SD	12	19.5	92	124-180	40-300	153
VOLVO	SD	12	n/a	40 s	150-300	n/a	160
YUTONG	SD	10 - 12	18	70-90	60 / 310-340	60-150	150-350

4 Case Study: Singapore

4.1 Public Transport Infrastructure

Singapore has 6.3 million residents. The city-state is part of the ASEAN region with a land area of 720 km^2 [48]. It is ranked as one of the most densely populated countries in the world after Macau and Monaco. With a demographic increase of nearly 100 % in the last 30 years and limited geographic land capacity, an efficient public transportation system is essential to meet the increasing mobility needs of local residents.

Singapore current public transport modes include buses, taxis and rapid transit system (RTS). RTS encloses both mass rapid transit (MRT) and light rail transit (LRT). As shown in Figure 4.1, buses are the most used mode of transportation in Singapore. In average, 3.9 million passenger trips are done daily by bus. After multiple bus network enhancement programs [49], Singapore counts 4 bus operators managing more than 350 service lines and 5500 diesel buses transporting commuters over 90,000 km of roads [50, 51].

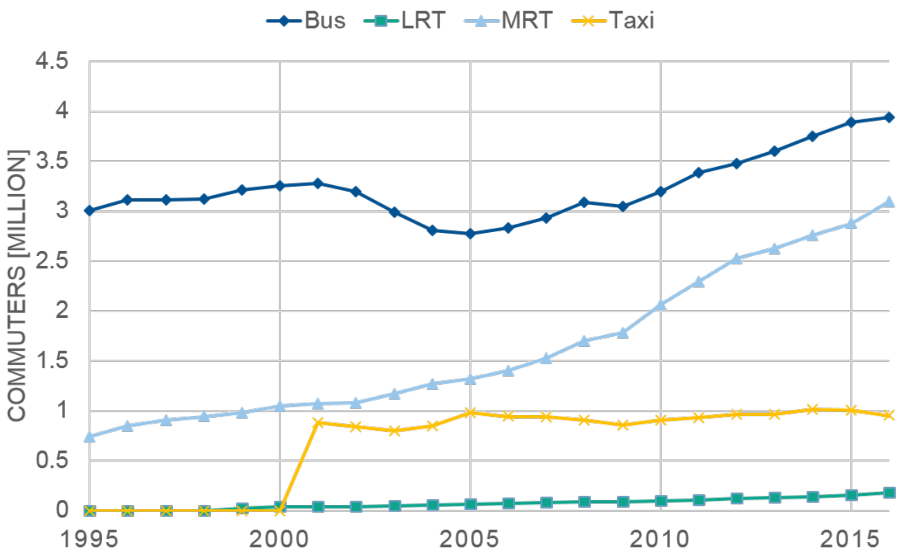


Figure 4.1: Daily public transport ridership in Singapore (1995 to 2015) [52].

Facing area scarcity and resources shortage, in an attempt to tackle the infrastructural, socio-economical and ecological overload, the Singaporean government decided to cap the vehicle growth to 0 % in 2018 [14, 53]. On the other hand, a unified payment system across all bus and rail operators was implemented using smart fare cards, enhanced with NFC technology, that allows passengers faster boarding and alighting. In addition, Singapore invested in the improvement of its express routes to tackle congestions and to ensure quicker driving journeys. All these efforts resulted in a well-managed traffic on the roads, compared to both developed and emerging cities.

4.2 Power System

Motivated by the instability of the oil price during last decades, Singapore operated a major shift in its power generation. As one of the signatory parties of the COP 21, Singapore is also engaged to reduce its particle emission levels of 2005 by 36 % until 2030. To reach this goal, strategies are being developed to encourage green growth opportunities in different sectors such as power generation, industry and transport [51].

The power-generation mix of Singapore was composed of 81.5 % oil and 18.5 % natural gas in the year 2000. In 2017, petroleum products represented only 0.6 % of the total electricity generation and 95.2 % generated from natural gas with an additional 4.0 % from renewable energies (mostly photovoltaic (PV)) [48]. 72 % of the total electricity production was attributed to combined cycle gas turbines, co-generation plants and/or tri-generation plants.

Singapore consumes 49.6 TWh of electricity per year. Transport-related activities are consuming up to 3.4 TWh (6.9 %). The national electricity generation capacity in 2018 has reached 13.6 GW while consumption power peak is still at 7.5 GW [54]. Led by PV, installed capacity from renewable energy is accountable for 0.1 GW [55]. Singapore average grid emission factor is stable since 2014 at around 0.4244 kg CO_2 / kWh according to the Energy Market Authority (EMA) as shown in Figure 4.2. In comparison, China electricity production is based mainly on coal up to 72 % in 2015 according to the U.S. Energy Information Administration, resulting in 1 kg CO_2 / kWh grid emission factor. In 2016, the US electricity mix was composed mainly of gas (33.8 %), coal (30.4 %), nuclear (19.8 %), and renewable energies (15 %), resulting in a grid emission factor of 0.4528 kg CO_2 / kWh [56].

These values suggest that Singapore has an energetic infrastructure capable to support transition towards electric mobility. The eventual increase of PV and renewable energies in the Singapore electricity mix can further contribute to the sustainability of electric mobility on a long-term basis [14].

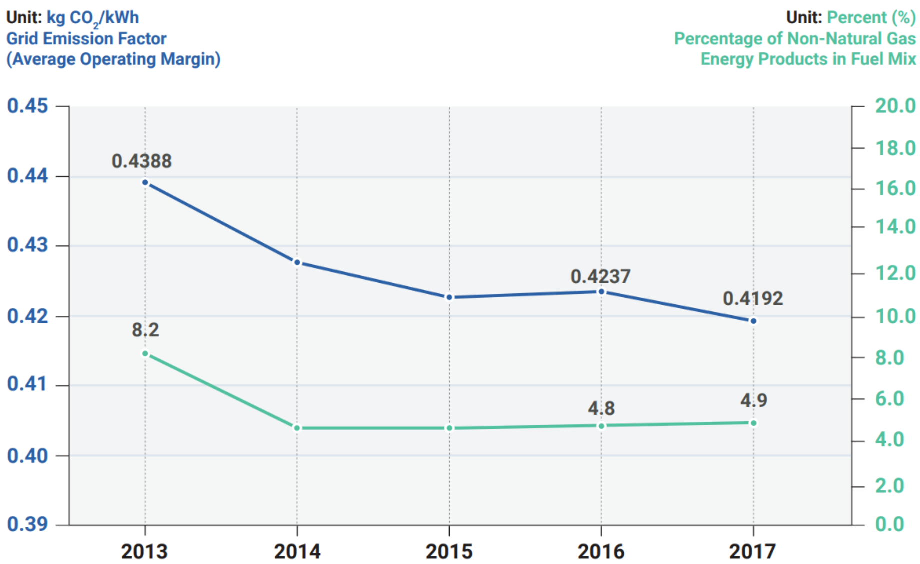


Figure 4.2: Overview of the energy cleanness in Singapore (2013-2017 [55].

4.3 National Journey towards more Sustainability

Since 2011, the Land Transport Authority (LTA) has started a journey to make Singapore a "Living Laboratory" [51] for the adoption of new mobility technologies such as electric vehicles. Various studies and national policies were initiated by the LTA to promote public transport and ensure a more sustainable mobility to the city-state such as the "Land Transport Master Plan" [57] and "Smart Mobility 2030" [58]. In 2015, after both previously introduced projects, the government launched the "Sustainable Singapore Blueprint" putting the focus on greener vehicles to promote sustainability and liveability under resources constraints.

At multiple occasions, the fact that buses and taxis public fleets have the biggest potential to be fully electrified in Singapore in the next years was stated. Replacing conventional diesel buses with electric buses is considered an important lead to decrease air pollution, and it was shown that it will result in a 56 % emissions reduction per vehicle [51]. The Energy Research Institute (ERI@N), part of the Nanyang Technological University (NTU), was commissioned by LTA to draw up the "Singapore 2050 road map" to a green mobility transition [59].

Different test beds and trials were initiated by LTA and EMA. As the country is gaining more experience with different new technologies, the trend towards electric buses is expected to increase in the next years.

4.4 Electric Buses On-Field Trials

4.4.1 First Electric Bus Trial

Different collaborations between researchers, transportation authorities and bus manufacturers brought in multiple trials on Singaporean roads [60].

The first official deployment started in November 2016 with one BYD K9 electric bus (324 kWh, 80 passengers, wired slow charging) until May 2017, part of the test bed initiated by LTA and the Economic Development Board. The BEB was put to service on bus lines 15, 17 and 119, with different lengths. Since the test was encouraging [51], LTA called a tender for the purchase of 50 hybrid buses and 60 pure electric buses (Contract Ref. PT323), after the approval of the parliament [23].

By the end of 2017, 50 diesel hybrid buses from Volvo were bought for 30 million SGD and are planned to start service at the second half of 2018. In October 2018, LTA awarded for 50 million SGD worth of contracts to three suppliers. BYD was awarded a contract for 20 single-deck BEBs. ST Engineering Land Systems (ST Kinetics) as well, was awarded a contract for 20 single-deck BEBs. Finally, Yutong-NARI Consortium won the third contract to supply 10 single-deck and 10 double-deck BEBs [61].

Awarding three tenderers aims at testing different electric buses and charging technologies. Every tenderer provides the needed charging infrastructure at both bus interchanges and depots. Wired charging and overhead pantograph technology are included in the awarded tender and will to be deployed by 2020 [62].

4.4.2 Autonomous Electric Bus

In January 2018, NTU announced a joint project with Volvo Buses to start trials on the first electric and autonomous bus in Singapore. Two 12-metre Volvo 7900 BEBs (19 kWh, 40 seats, roof-mounted fast charging) will be tested at the Centre of Excellence for Testing and Research of Autonomous vehicles (CETRAN), in a circuit simulating real conditions. The Swiss/Swedish leader group ABB provided the required charging infrastructure for the tested buses. "The NTU and Volvo partnership is also part of the collaboration between NTU and LTA under the university's living lab platform announced in October 2016. The living lab platform assesses technology maturity and road-worthiness, including the certification of the technologies for deployment on public roads" [63].

Many other prototypes were developed and tested in Singapore such as Arma by Navya SAS, ultra fast-charging Blue Solutions Flash Shuttle by NTU, and the GRT by SMRT and 2GetThereAsia [64].

4.4.3 Private Sector Leads

Following the public authorities shift toward electric buses, the private sector started its own transition in Singapore. July 2018, the bus-pooling provider ShareTransport launched a 1-year trial of an electric 7 m C6 BYD coach (135 kWh, 24 passengers). This service collects commuters from and to homes and offices, representing an in-between alternative to public buses and taxis. The BYD C6 bus will be operated from pick-up points near Corporation Dr to drop off points along Shenton Way [65].

4.5 Data Acquisition for the Case Study

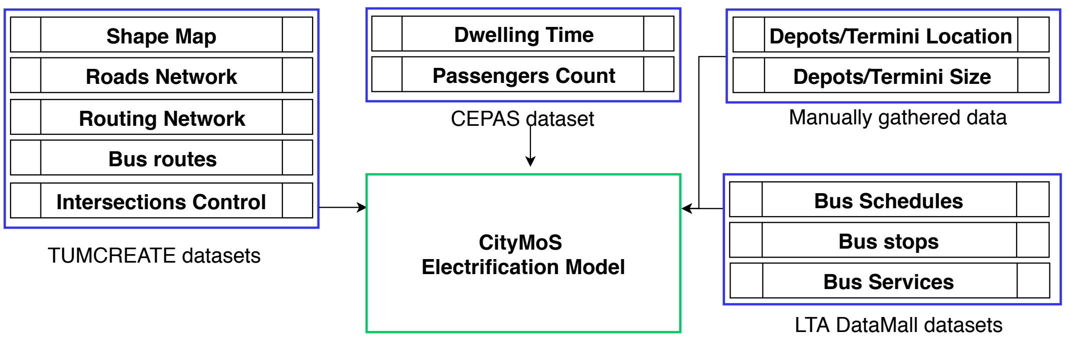


Figure 4.3: Summarising diagram of all datasets used for the Singapore public buses electrification simulation.

Simulating a city-scale bus network requires an important amount of data, including bus schedule, city infrastructure, depot and termini locations. Applied to our current case-study, four main data sources were used to achieve the presented results in Chapter 6: CEPAS dataset, LTA DataMall, AIDA team's data collected from previous works, and online open source data. However, this simulation can be exported and applied on any region, as long as this data is available. A general overview of the data sources can be found in Chapter 4.3 and data processing pipeline is given in Figure 5.14.

4.5.1 Contactless e-Purse Application (CEPAS)

In Singapore, commuters need an contactless fare card to pay public transport fees, commonly referred to as EZ-Link. Card readers are installed in every bus and at every railway station. Passengers have to tap in and out with their card upon boarding and alighting in buses or MRT or LRT station. Fees are calculated when they exit the bus or the railway station and are deduced from their main prepaid balance. "CEPAS" database records every passenger transaction when tapping his EZ-Link card (entry and exit).

LTA provided TUMCREATE with data from the period between 19.08.2013 to 21.08.2013. The data consists of a set of around 12.8 million journeys, equivalent to 3.2 million passenger journey daily. It includes time records of all bus trips with aggregated boarding and alighting passenger count at every station. Since card readers are located inside the buses, the data collected includes also temporal and spatial data for each trip. The distribution of the commuters journeys during the day can be seen in Figure 4.4. From the CEPAS dataset, it was possible to derive passengers flow and to model electrification scenarios [14].

Passengers Flow

Day-long high resolution data on boarding and alighting passengers at every bus stop for every bus service was extracted. All alternative public transports were filtered out and only bus trips were kept. The data was processed and aggregated to 30 min intervals and fed to the simulation in order to model commuters flow and calculate both dwelling time at every stop and passengers count in the bus for every terminus-to-terminus journey. The final CSV file contains bus stop code, bus service, start time, end time, boarding, and alighting counts.

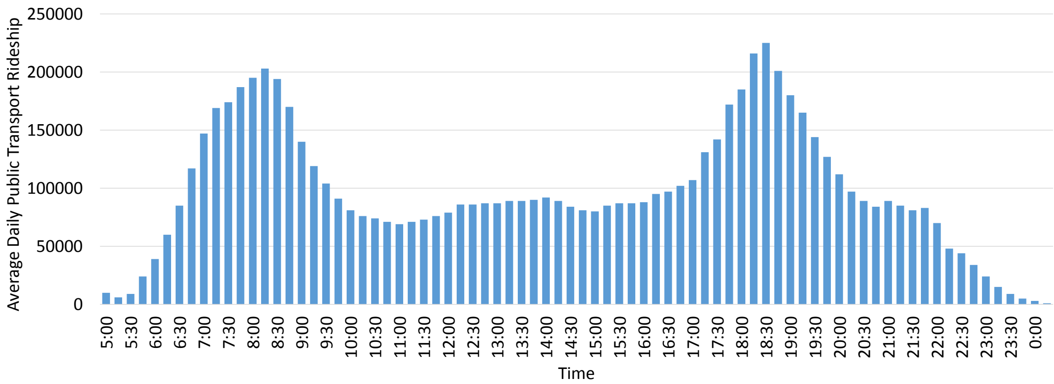


Figure 4.4: Singapore public buses ridership aggregated over 30 minutes [50].

Energy Consumption Model

The CEPAS data was processed and used by Gallet et al. to calculate the energy consumed by conventional buses in [14]. The longitudinal dynamics model was developed mainly based on the CEPAS data by simulating the buses driven distance extracted from the boarding and alighting data. This study was the first to approximate the energy consumption of a a pure battery electric bus fleet in Singapore. The results were used in this work as a benchmark and compared in the validation process.

4.5.2 LTA DataMall

The LTA DataMall is a portal providing access to transport datasets to enable public transport solutions and new services, available online [52]. It is meant for third-party developers and researchers to promote collaboration with LTA. Through this online interface data such as bus routes, bus services, bus stops, estimated travel times, and bus arrival times can be acquired for free. Bus stops, routes and bus schedules at termini were collected via the LTA DataMall and used to obtain the current results.

4.5.3 Singapore Infrastructure

Data from Previous Works

Singapore maps and networks were available from previous TUMCREATE works. It contains all Singapore infrastructure networks, as shown in Figure 4.5. All data was processed and adapted to fit the simulation input format, including

- routing network: connecting all pairs of geo-referenced nodes representing the real-world roads,
- road network: containing lanes composing the roads created by two connected nodes from routing network, on which vehicles models can drive, overtake. . . ,
- bus routes: describing lanes and bus stops assigned to a certain service in a unique direction,
- 3D building representation: drawing a shape of all buildings in Singapore.

Figure 4.5: Singapore roads (blue) and routing (pink) networks in CityMoS.

Manually Gathered Data

Termini and depots locations were determined semi-automatically, after crossing different sources such as Google Map, Google Earth, sgwiki.com, wikipedia and OpenStreetMap. Given the limitations of the data collected stated in the following Section 4.5.4, for the case of termini and depots locations that are unchanged since 2013, Google Maps and OpenStreetMap were used to confirm the approximate location with the help of the CityMoS Map Editor.

Termini and depots relocated since 2013 were compared to Google Earth 2013 satellite shots. Thus, it was possible to compare with 2013 state, to adapt the infrastructure to the same temporal stand, and to ensure the data homogeneity with Singapore bus network in 2013.

4.5.4 Data Assessment

The CEPAS dataset does not contain any information about off-service bus trips (also called dead-heading trips), since no passengers are involved in these journeys.

Also, the CEPAS dataset and the Singapore infrastructure networks are only representing the bus operations of LTA network in 2013. Unfortunately, due to the unavailability of more actual data, this year was used as reference.

Singapore road map is not perfectly similar to reality. Given the size of the studied area, the data was only generated automatically and could not be checked exhaustively for bugs and errors. Minor deviations from real-world were at certain occasions noticed and debugged. This is further detailed in Section 5.5.

5 Methodology

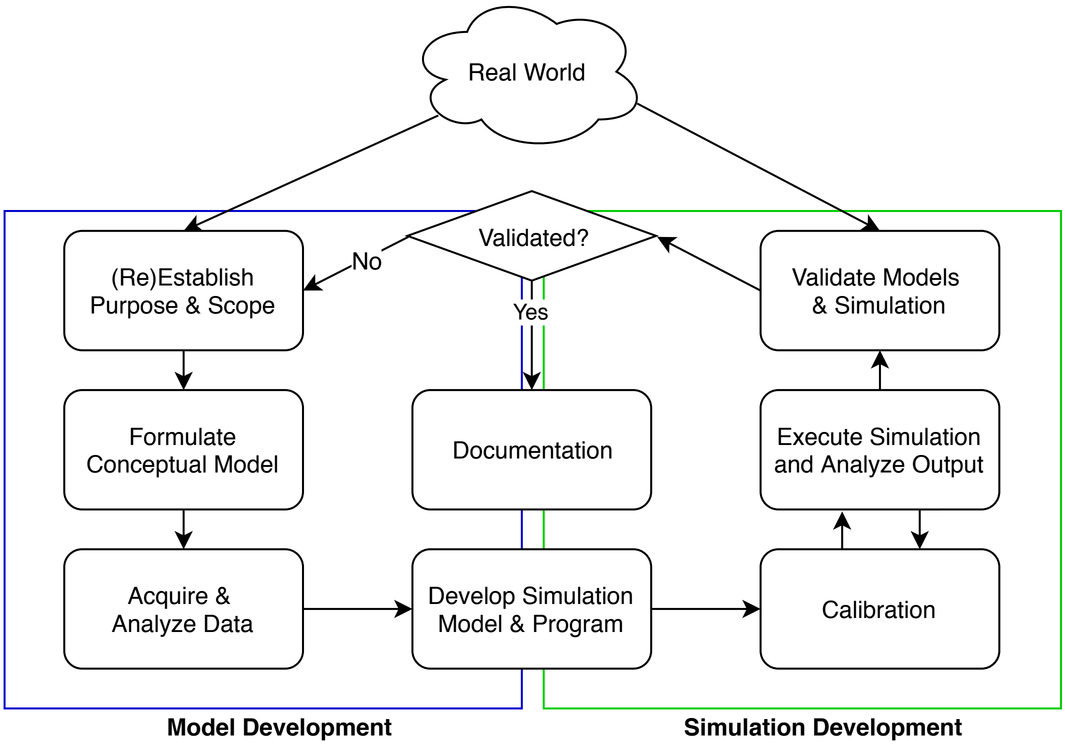


Figure 5.1: Modelling and simulation process overview [66].

According to the modelling and simulation process, represented in Figure 5.1, the purpose and scope of this work were first defined in Chapter 1. After a deeper research on the technologies and concepts presented in Chapter 2, scientific literature was reviewed and summarised in Chapter 3. With the analysis of Singapore transport and energy infrastructure described in Chapter 4, a better understanding of the models to implement was achieved. In this chapter, focus will be set on the rest of the flowchart steps.

First, the development of electric buses, charging stations, depots, and termini models will be described in the implementation Section 5.1. The preparation of the simulation input data (described in Section 4.5) and how it was connected to the program is introduced in Section 5.2. Once the simulation running, output data is collected and processed according to the method introduced in Section 5.3.

Due to the complexity of the case study, once all models were implemented and the simulation running, an intensive debugging phase was needed to ensure a plausible calibration of the models and to provide a stable simulation environment. CEPAS dataset was used to calibrate the simulation in Section 5.4. The validation process against scientific literature is reported in Section 5.5. Finally, in Section 5.6 the assumed strategies and parameters are grouped.

5.1 Implementation

In the following section, an agent-based, city-scale electric public bus network simulation is described. It aims at modelling the electrification of conventional diesel-fuelled public buses and at studying the impact of this electrification on the energy infrastructure and network operations. To ensure a realistic simulation, acceptable for bus network operators and commuters, the simulation takes as input the unchanged current city infrastructure (roads, bus routes, schedules, bus stops, termini and depots location).

According to this input data, passengers are modelled to be able to board and alight in conventional or electric buses at bus stops and to be transported from one location to another in a predefined direction, within a bus line. Bus operations should be simulated as near as possible from the business-as-usual scenario in the real-world.

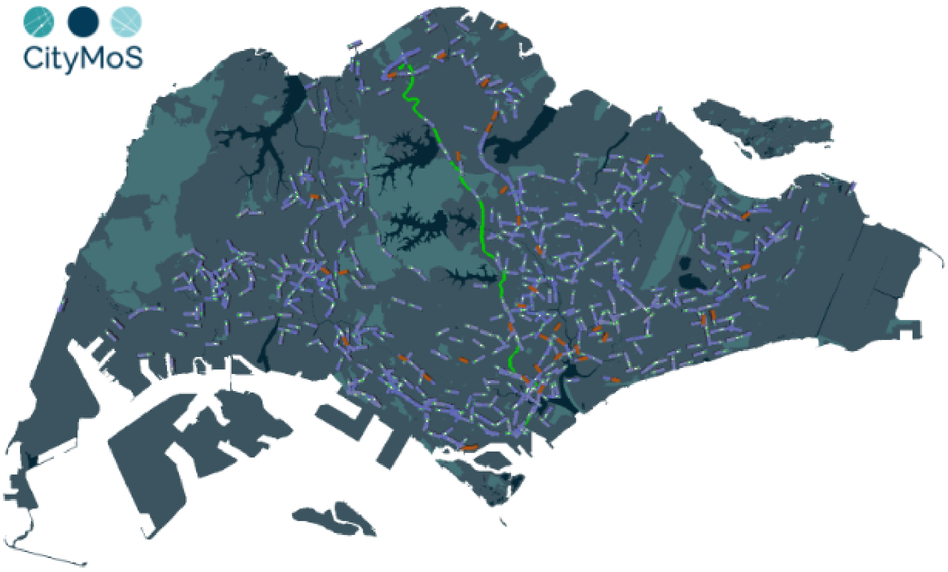


Figure 5.2: Singapore-wide electric public buses simulation in CityMoS.

5.1.1 CityMoS

The project was implemented in the CityMoS framework [67, 68], a microscopic agent-based simulation platform developed by TUMCREATE Ltd. CityMoS (City Mobility Simulator), previously SEMSim (Scalable Electromobility Simulation), is an extensible traffic modelling framework written in C++. It was developed as a programming environment that facilitates researching on topics related to vehicle types, infrastructure topologies, and their interactions together in real-world-like system [69].

It is capable of simulating a large number of driver-vehicle agents with distinct characteristics, in a predefined city environment and infrastructure such as roads, buildings, and traffic. It offers the possibility to model large city areas while offering a high level of details, supported by high performance computing capabilities.

CityMoS has been previously used for investigating the potential of taxi sharing in Singapore [70] and for determining ideal location of charging stations for electric vehicles [71, 72], in the scope of previous research works at TUMCREATE.

Simulation Capabilities

Agents represent encapsulated classes describing a specific behaviour, interacting with both other models and agents. This programming architecture based on an agent-based approach gives a great level of flexibility and enables the modelling of complex systems as a composition of simple sub-systems interacting with each other.

CityMoS is based on an event scheduling concept, where time is discretised to the millisecond and events are scheduled and executed accordingly. All agents state changes are done synchronously with the execution of triggered events. In the case of electric buses, the two main events responsible for the progress of the modelled agents are the dispatch events derived from the LTA bus schedule in Singapore and the event updating the position of the agents on the roads. At the beginning of the simulation, all schedules are translated into departure events. Buses are dispatched, operated, and charged when scheduled events are triggered according to the incremented simulation time. The simulation continues running as long as the event queue is not empty. Once all pre-scheduled events executed, the simulation ends and all agents destroyed.

CityMoS can simulate thousands of buses driving at the same time during peak hours over long periods of time (up to 26 days) and outputs data on the agents state every time step. Parallel computing techniques are used to accelerate this large-scale simulation.

Road Infrastructure

To model a specific case-study, CityMoS requires as input the location map, roads, and routes. The network is implemented as a map of nodes defined with geographical coordinates and edges. CityMoS roads are composed of routes included in the routing network input file. From the road network configuration file lanes composing these routes are extracted.

Agents navigate from node A to a destination node B through pre-calculated nodes. Each route contains information about the distance (calculated according to the Dijkstra Contraction Hierarchies algorithm), the road geometry, or the slope of the road (being implemented at the time of writing this work). More details on roads infrastructure models are given in Section 4.5.

Graphical Interface

Besides the computation capabilities offered by this simulating platform, it offers a graphical interface that was further developed during this work to enhance debugging efficiency and visualisation capabilities. The 3D graphical interface offers high granularity visualisation including roads, traffic, buildings, and statistics on content of termini, depots, bus stops and driving buses. An overview of Singapore map with a highlighted bus route in green and oversized buses in purple can be seen in Figure 5.2.

5.1.2 Battery Electric Bus Model

Vehicles, including buses, are modelled as driver-vehicle-unit (DVU) in CityMoS. A DVU is the combination of both a conveyance technical specificities and driving behaviour on the road (driver included or autonomous). As shown in Figure 5.3, DVU module is the parent class for buses models. In the figure, the building blocks represent the classes created, modified, or considered in the scope of this master thesis. The DVU class was inherited from previous works. It can be best described as "vehicle", without any reference to cars, buses, or any specific behaviour to only one vehicle type.

Electric bus model (SElectricBusDVU) is derived from SDVU, SBusDVU, and SBusDVUWithPassenger classes, developed in previous works at TUMCREATE, inheriting all their behaviours (according to the inheritance concept in C++). All agents are initially created by the SBusTrafficGenerator via the AgentFactory and are destroyed at the end of the simulation.

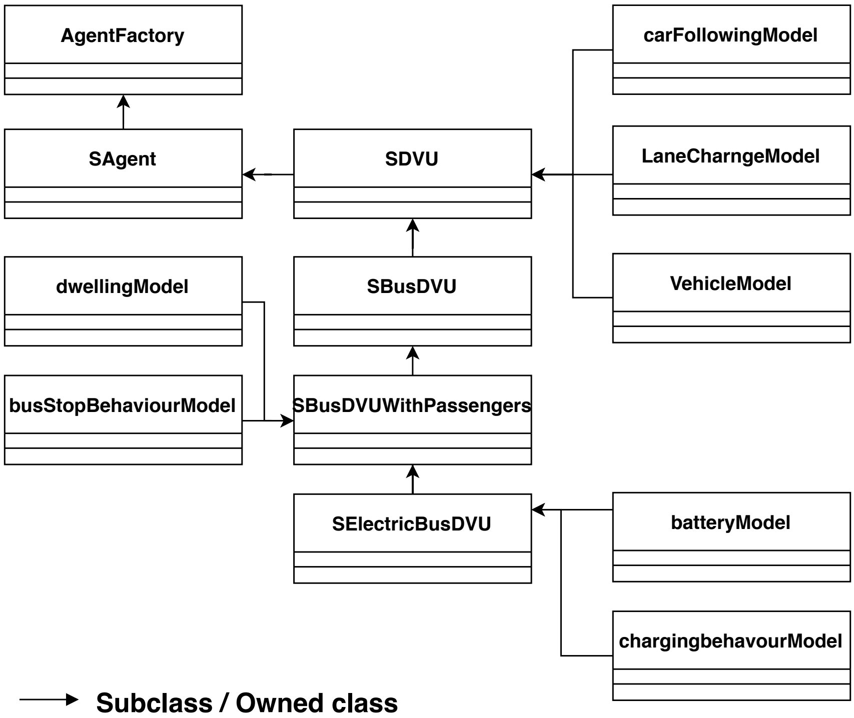


Figure 5.3: UML class diagram of CityMoS electric buses model.

Driver Model

A DVU driving behaviour is based on four models. First, there is the car-following model, referred to it as Intelligent Driver Model [73]. Then, there is the "MOBIL" model responsible for the lane changing behaviour of the agents [74]. Finally, there are the intersection model, and the routing model.

The car-following model calculates the desired speed and acceleration, while taking into account the movement of other agents (e.g. road traffic) and the driving environment (e.g. traffic lights). The lane changing behaviour controls the position of the vehicle and updates it every time step while taking into account the movement of other vehicles and their own repositioning.

The intersection model controls the behaviour of the DVU at road crossings and traffic lights. The routing model is responsible for routing the vehicle from its starting point to its destination, according to its pre-calculated itinerary.

Vehicle Model

The vehicle model holds information on essential characteristics of the bus such as size, weight, drag coefficient, front area, carbine volume, passengers capacity, HVAC. For electric buses, specific BEBs characteristics on the battery are included.

In this work, scenarios with mixed fleets were studied, including different combinations of conventional and electric buses. Two different electric bus types were also modelled: SD with 70 % ratio and DD with 30 % ratio of all electric buses count. An overview of the vehicle model of each electric bus type can be found in Table 5.1.

Table 5.1: Modelled electric buses types in CityMoS.

Bus Type	Ratio	Curb Weight	Front Area	HVAC Power	Battery	Passenger Capacity
Single Decker	70 %	12.5 t	8.3 m^3	10 kW	90 kWh	60
Double Decker	30 %	17.5 t	10.35 m^3	15 kW	150 kWh	80

Dwelling and Bus Stops models

A Bus starts its journey at a terminus A to finish at terminus B. It stops at every bus stop included in the service route assigned to that bus trip until reaching its destination. Bus stops are identified by a unique LTA code and are modelled to accept commuters. Passengers waiting for specific line buses are simulated according to the passengers input file generated from the real-world CEPAS dataset, as introduced in Section 4.5.1.

According to the alighting and boarding passengers count, with regards to the capacity of the bus and place availability, the dwelling model calculates the dwelling duration. Within this model, passengers capacity, alighting and boarding speed are defined for every bus type. Alternatively, the simulation configuration files offer the possibility to set a fixed dwelling time for all buses.

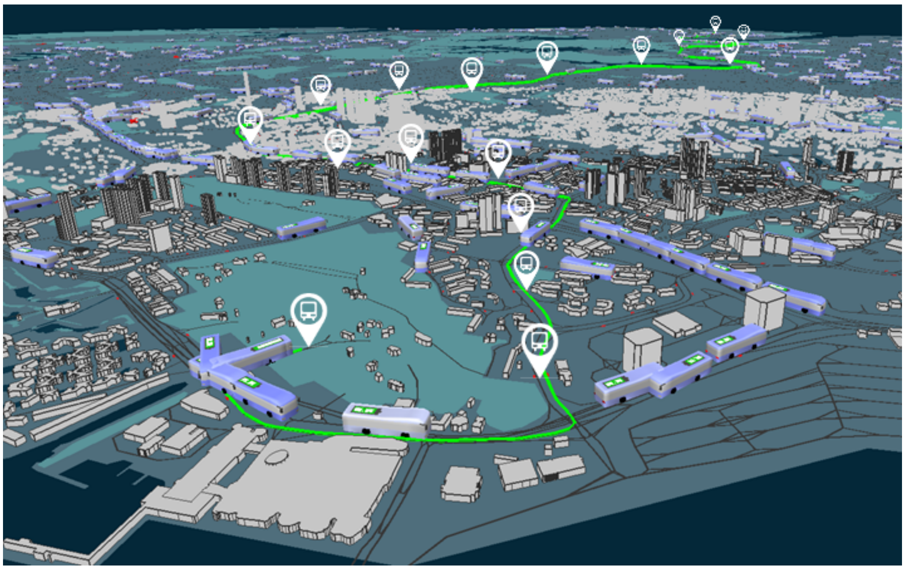


Figure 5.4: CityMoS bus route with marked bus stops.

An overview of driving electric buses in the CityMoS simulation is presented in Figure 5.4. The green line represents the roads included in one bus route. Bus stops included in the scheduled bus terminus-to-terminus trip are marked with white icons.

Stateful Electric Bus Model

Bus operations were previously modelled with 100 % fossil-fuelled buses. Buses not driving were deleted from the simulation to save memory. When a bus was needed for dispatch, a new agent was created via the traffic generator. The newly created vehicle was put on the road, drove from the departure terminus to the destination terminus according to the scheduled route, to be finally destroyed at arrival. This was the life-cycle of a bus agent, represented in the left flowchart of Figure 5.5.

In order to study queuing and dispatching of electric buses in termini, depots and charging station and to calculate the energy consumed over hours and days of operation, a new life-cycle for buses agents had to be implemented. In the new modelled bus operations, buses are created once at the beginning of the simulation by the traffic generator and are only destroyed at the end of the simulation, when the event stack is empty. The new electric DVU life-cycle is represented in the right side of Figure 5.5. The created buses are identified by unique IDs that will enable tracking the state of BEBs along the operation days.

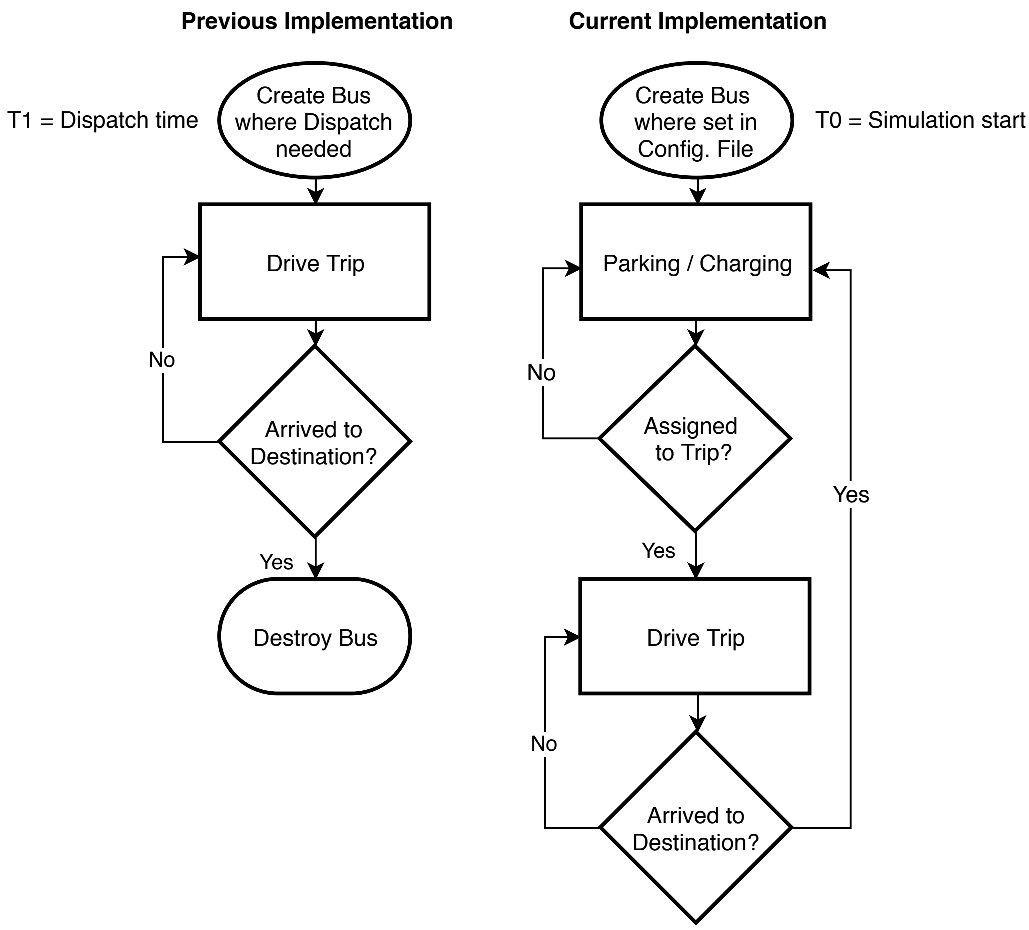


Figure 5.5: Stateful electric buses operation versus previous model.

Energy Consumption and Battery Model

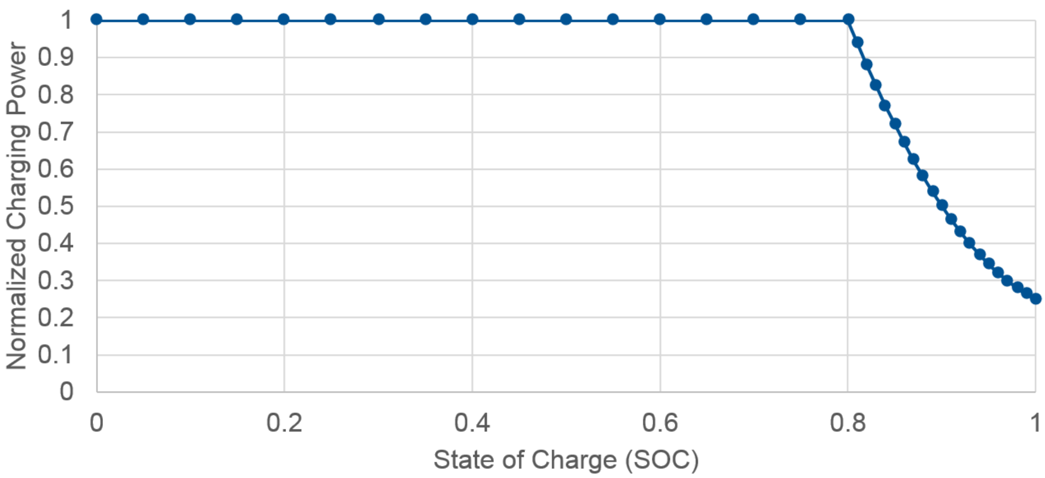


Figure 5.6: Electric bus charging curve in CityMoS [75].

The energy consumption model of the DVU is based on longitudinal dynamics, derived from the vehicle characteristics and the sum of its driving resistance forces (inertia, drag, roll and climb), in addition to the HVAC and auxiliary energy consumption. Energy exchanges from the bus battery are modelled via 4 connectors to the battery: HVAC consumption connector, motor energy connector for consumption and recuperation, auxiliary and charging connectors. According to the state of the electric bus (Table 5.2), it is switched off, recuperating (positive) or consuming (negative) energy.

Table 5.2: Overview of the electric bus states and battery connectors.

SDVU States	HVAC	Motor	Auxiliary	Charger
(0) Driving	Negative	Negative	Negative	Off
(1) Parking	Off	Off	Off	Off
(2) Charging	Off	Off	Off	Positive
(3) Breaking	Negative	Positive	Negative	Off
(4) Queuing	Off	Off	Off	Off
(5) Dwelling	Negative	Off	Negative	Off

The simplified battery model is based on a previously developed class for electric vehicles. It includes a maximum capacity, a 95 % constant efficiency in charging and does not take into account any deterioration over the operation time. Battery temperature, C-rate, or state of health (SOH) were not taken into consideration in the present work. However, an upper and lower SOC limit were set to simulate a battery safety mechanism.

If energy was consumed from the battery and the SOC level is under 100 %, the modelled electric buses will ask for charging. Modelled charging power of the battery is linear as long as the SOC is under 80 %. Once the SOC is above a predefined threshold value, the charging power is capped until the battery is charged, according to Equation (5.1). In the Figure 5.6, the blue line represents the charging power curve of the simulated electric buses relatively to the SOC.

$$P_{charger}(SOC) = 2.5 \cdot SOC^2 - 26.25 \cdot SOC + 14 \tag{5.1}$$

5.1.3 Charging Strategy and Infrastructure

Charging Strategy

In the developed simulation, charging stations are available at depots and termini, enabling overnight and end-station terminus charging. The number of chargers needed at every charging station was tailored to the simulated scenarios, as described in Section 5.4.

Even if the on-route charging seems to offer a "superior operation compared to other BEB configuration" according to Mohamed et al., most of the studies done on the topic conclude that end station charging between two consecutive journeys with overnight depot charging are the best way to move forward with the question [11, 27, 35].

Charging Station Directory

The charging station directory is the aggregating class, to which all charging stations models are connected, as shown in UML (Unified Modeling Language) Figure 5.7. The presence of a directory enables to iterate over all charging stations in the simulation.

In this work, a fixed curtailment value was implemented that enables all charging stations to decrease their power demand by a certain percentage at specific times of the day. This can be used to model electric grid pressure, for example in case of power generation failure. It represents the interface to further studies on the impact of electric buses on the grid, and vice versa.

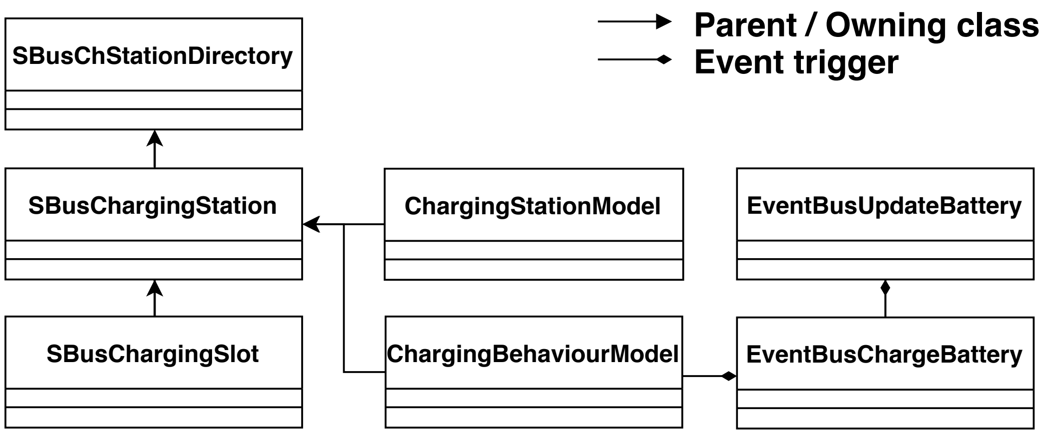


Figure 5.7: UML class diagram of CityMoS charging station models.

Charging Station Model

The charging station model consists in a predefined number of chargers, that can be owned by either a terminus or a depot. In this work, we assume that the number of chargers is inferior to the number of buses that be accepted in the depots and termini. Thus, buses are sharing charging infrastructure with a limited number of chargers installed.

An electric bus checks-in at the electrified terminus or depot. If its SOC value is under a pre-defined threshold, it is accepted in the charging station. When the BEB has finished charging, it will be idling (parking) and awaiting the next assigned trip.

Once accepted in the charging station, an electric bus is added in a waiting queue. It can be assigned a charging slot, if no buses are competing with it. If no charging points are available, the bus will be waiting until one becomes free. This second flexibility point enables experimenting on different queue prioritizing strategies as studied previously by De Filippo et al. [13].

Charging Queue

Buses in the queue wait until they are allowed to access a free charger. Every time a bus finishes charging or a new bus checks-in or checks-out from the charging station, a check for free chargers is made.

In case of an available charger, a bus is selected from the waiting queue according to one queuing strategy. Prioritisation strategies that were implemented in this work are:

0. Random: a bus in the waiting queue is picked up randomly.
1. first-in first-out (FIFO): first bus arrived to the charging station charges first.
2. last-in first-out (LIFO): last bus arrived with shortest queueing time is prioritised.
3. highest SOC first (HSOC): the bus with highest SOC is given priority to charge. This queuing strategy is according to De Filippo et al. [13] the one ensuring the shortest average waiting time for all buses.
4. lowest SOC first (LSOC): the bus with the lowest SOC is promoted to charge first.

Charging Slot Model

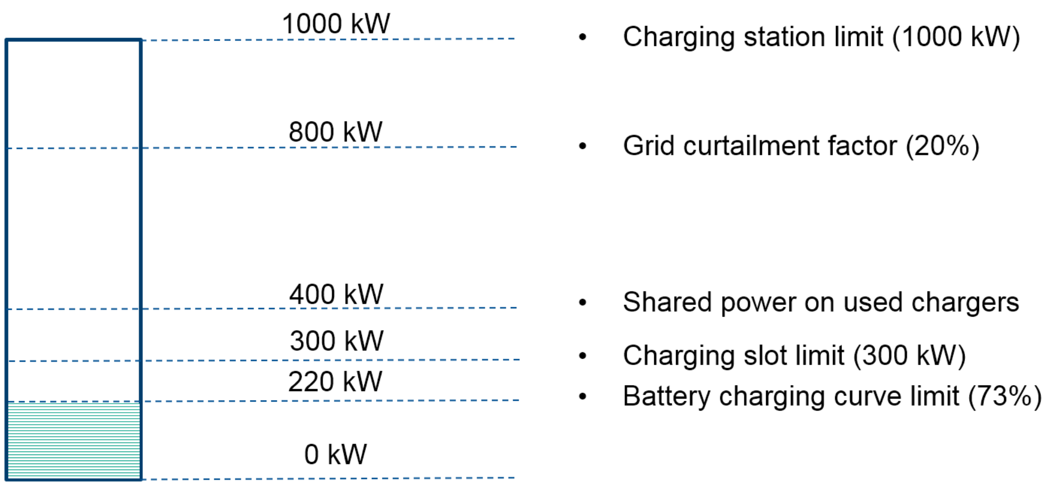


Figure 5.8: Example of power calculation for a charging station with 2 chargers.

The charging slot model is defined by its charging station and its maximum charging power limit, modelling the upper hardware limit of chargers in real life. The charging power is calculated according to four different variables, as shown in the example of a charging station with 2 chargers in Figure 5.8.

First, the battery charging curve is modelling the electric vehicle battery charging limits, as shown in Figure 5.6. Then, the charger maximum power is predefined from the beginning of the simulation. Third, the charging station maximum power is divided by used chargers, modelling the hardware upper power limit of the charging station. Finally, the grid curtailment enforces all charging stations to decrease their power demand by a certain ratio if needed. This behaviour is enforced by the Equation 5.2.

$$P_{slot} = min((Factor_{curtailment} \cdot Power_{station})/N_{chargers}), Power_{charger}) \tag{5.2}$$

5.1.4 Depots

Bus depot or garage is a bus parking location where buses are stored and maintained when they are off-service or overnight. They are considered essential facilities for bus operations, enabling maintenance, refuelling, storage, and in the case of electric buses, charging. If not in dispatch, a bus can be parked in a terminus or it can be sent back to the most appropriate depot.

An UML flowchart representing a high level overview of the depot models and classes is shown in Figure 5.9.

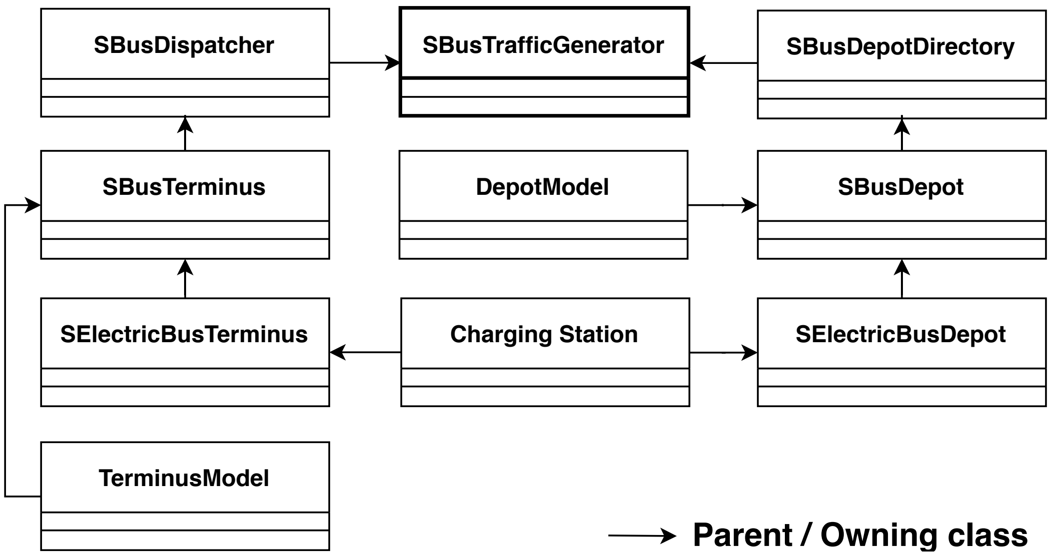


Figure 5.9: UML class diagram of CityMoS termini and depots models.

Depot Directory and Model

The depot directory is the aggregating class of all depots instances. It enables iterating (looping) over all depots in the source code. With the help of this class, it is possible to look for nearest depot or to find the most adapted depot to send bus back to.

The main characteristics of each depot are stored in an instance of the depot model, identified by a name and a LTA code. Every instance describes the depot size, its capacity (i.e. parking places), its location and the number of buses initialised at the beginning of the simulation.

Every depot in the simulation prioritise buses to send to termini according to a chosen dispatch strategy. Basic strategies implemented during this work are: RANDOM, FIFO, LIFO, HSOC, and LSOC. The scenarios presented in Section 5.7 are all set with HSOC as dispatch prioritisation strategy.

Electric Depot

Although depots can be conventional or electric (with an additional charging station attached to it), only electric depots were considered in this work.

In non-electrified depots, the vehicles are parked immediately, without consideration if buses are electric or conventional. In electrified depots, diesel buses are parked after check-in. Electric buses are forwarded to the charging station to be accepted in the chargers queue or to be refused and sent back to parking, if SOC threshold is not reached.

5.1.5 Termini

A termini are defined as start or end stations of at least one bus line. Bus routes have mainly two termini, yet some of them are circle lines starting and ending at the same terminus. An UML flowchart representing a high level overview of the terminus models and classes is shown in Section 5.9.

Terminus Model

The terminus class is one of the most important classes implemented in the buses operations. This class is responsible for the dispatch procedure and the respect of the given operating schedule. It enables placing buses in service clusters (pools), reserving a vehicle for an upcoming trip, dispatching it when the scheduled time has come, and finally checking if the battery of the selected bus is charged enough to make the trip.

Service pools:
Bus pools are a concept that was implemented to model affinity of a bus to one service route during full operations day. While buses are in real-world mostly assigned to a unique bus route, they are also redirected to take over in critical situations in different services or termini (e.g. peak hours, accident, defects). Since there is no electric buses in Singapore and so, there is no dispatching schedule available, a dynamic system was modelled to determine which bus to send. In the modelled termini, buses are grouped according to their associated service pools, representing the line assigned to them.

Intra-terminus rebalancing:
If a service pool is too crowded in a terminus, an intra-terminus routine rebalances the average bus count by assigning one bus from the concerned service to the "Off service" pool. If the terminus is overcrowded and reaches its upper capacity, a send-bus-back-to-depot event will be triggered and a bus will be selected (according to RANDOM, FIFO, LIFO, HSOC, or LSOC algorithms) to return to the most suitable depot. In contrast, if a service pool is nearly empty, the terminus looks for a bus to assign to the drained service pool first from "Off service", then from other pools. If no buses can be extracted, a call for refill will be sent to the dispatcher. An overview of intra-terminus rebalancing strategies implemented is given in Figure 5.10.

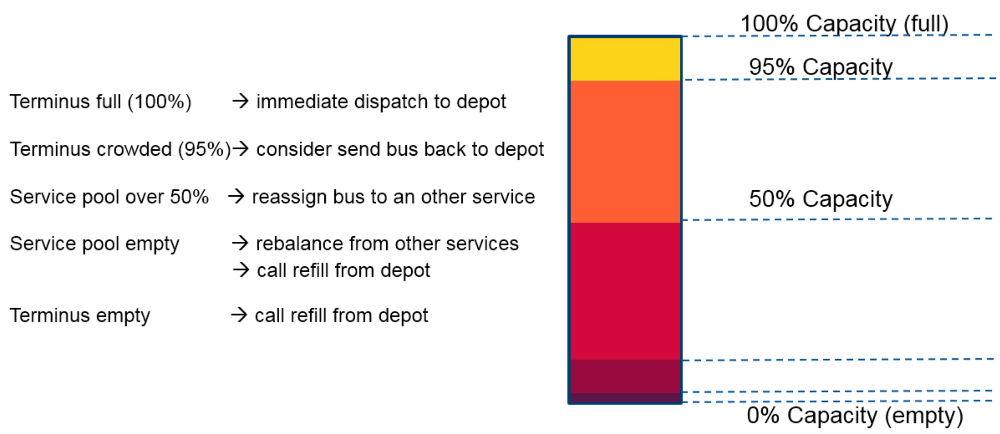


Figure 5.10: Overview of the rebalancing strategies implemented in the simulation.

Trip planning:
The terminus model is also able to reserve a bus in advance for a later dispatch event. In real life, bus operators plan the operation schedule of each bus in advance. Bus drivers are given a daily schedule of all journeys and breaks. Bus operators plan dispatch events in advance and determine which bus will be assigned for each trip, which results in a daily trip schedule for each bus.

In this master thesis, we only succeeded in pre-planning a bus trip 15 minutes in advance. A longer planning time period would require a more advanced planning model, specially to take into consideration buses that did not reach their destination first. During the reservation process, parked buses are prioritised. If no parked bus is available, a queuing or charging bus will be selected. Buses to be dispatched are prioritised according to the five algorithms: RANDOM, FIFO, LIFO, HSOC, and LSOC.

Range check:
The remaining range of buses is checked while selecting a bus for the next service trip. The terminus compares the remaining energy of the selected bus with the logged energy for the planned service and direction (see Section 5.1.6). Only if the range of the vehicle is sufficient it will be confirmed to drive the next trip.

If no buses are available, the terminus will check again later. When the scheduled dispatch event is triggered, the reserved bus is extracted and set to driving mode. If at that time, still no buses are ready for dispatch, the bus trip is aborted.

Electric Terminus

Electric termini are a subclass of conventional termini with an additional charging station. In case there are no buses parked in the terminus and a bus is needed to ensure an imminent trip, an either queuing or charging bus is extracted from the charging station attached to the terminus according to different prioritisation strategies: RANDOM, FIFO, LIFO, HSOC, and LSOC. If no buses could be extracted from the parking or the charging station, a call for refill will be sent to the dispatcher and check again later.

5.1.6 Bus Operation

Traffic Generator

The traffic generator is one of the first classes executed in the simulation and one of the highest instances in CityMoS, below the main function of the program and "core". It reads all configuration files to set up the bus operation environment (map, city networks...), initialising termini, depots, and creating all agents.

The traffic generator is also responsible for scheduling all predefined events of the simulation. All bus route schedules fed as input to the simulation are also converted into events and assigned to the involved termini. Once all the scheduled events triggered, the simulation ends.

Dispatcher

One level below the traffic generator, the dispatcher models the bus operator, organising the whole dispatching process. His tasks include coordinating the different agents, termini, depots and regulating the buses introduction and take off from to the road. It supports the bus operations to ensure the respect of dispatch timetables and to minimise the number of missed scheduled trips.

Traffic coordinator:
Its tasks include adding buses to traffic and notify their departure and arrival to the involved termini and depots. When their arrival is notified, buses are checked-in.

Inter termini/depots rebalancing:
The dispatcher is also responsible for the rebalancing of termini and depots. In some cases buses or depots are getting empty/full, when others are still full/empty. To avoid such unbalanced simulation state, the dispatcher is in charge of keeping buses count averaged in all termini and depots. It has the authority to initiate bus trips from a selected terminus or depot to another structure to adjust bus count, where an unbalanced state is detected (see Figure 5.10).

Energy logger:
The bus dispatcher calculates the average energy needed for every terminus-to-terminus journey in order to ensure every dispatched bus has enough energy to finish its trip in addition to an emergency reserves. It logs the energy demand per service, per direction, and per bus type. The energy needed is then calculated according to the rolling average of energy consumption of the 5 last driven trips, with an additional 50 % buffer energy. This process is also established to avoid reaching harmful SOC levels, set in the literature to 10 % [11], 20 % [76] and 30 % [19, 38].

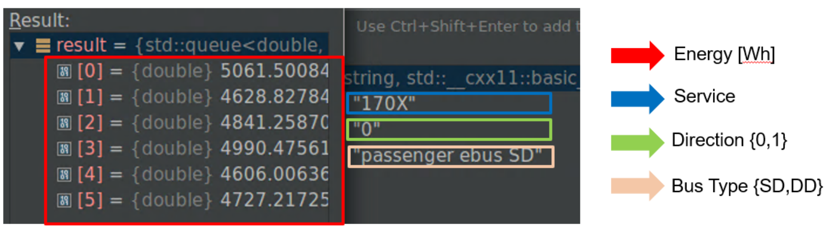


Figure 5.11: Centralised energy logging structure in the bus dispatcher.

Departure Summary Overview

In figure 5.12 summarises the main processes of all models and agents introduced previously, related to the departure of buses from termini.

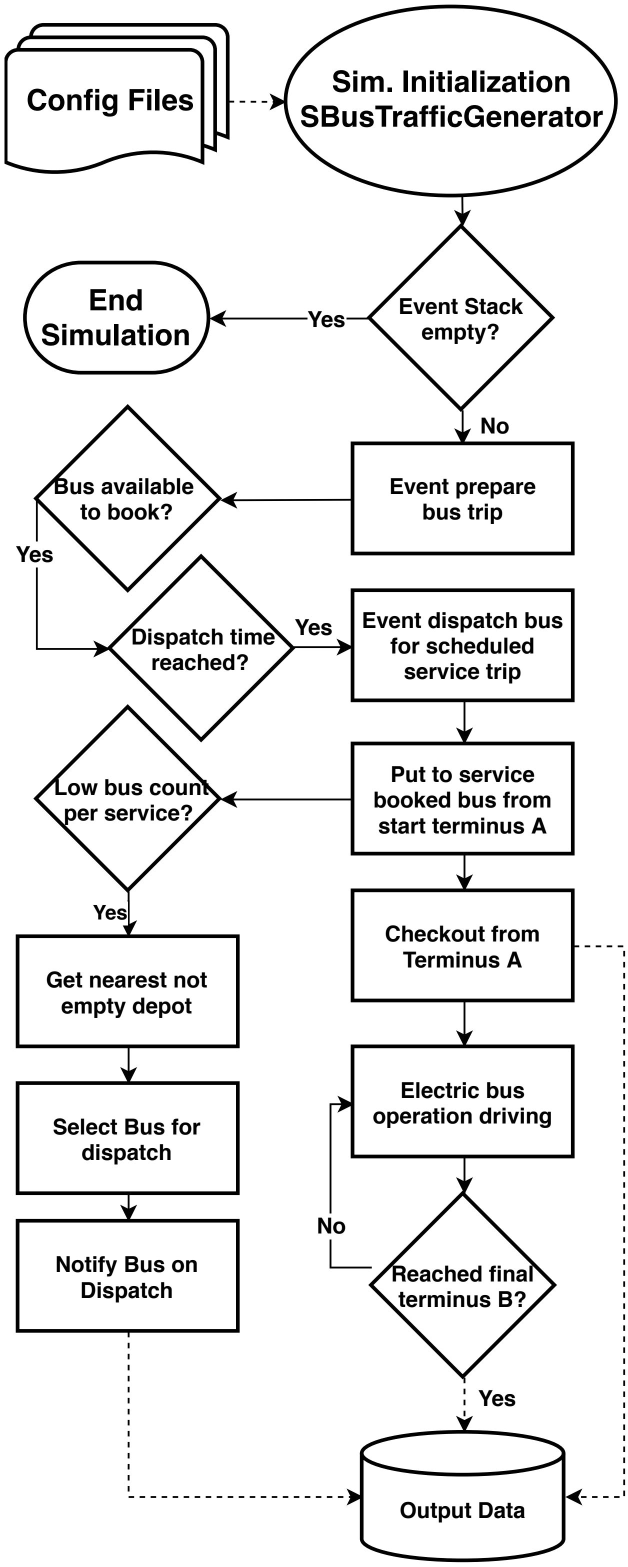


Figure 5.12: CityMoS simulation start and electric buses dispatch flowchart simplified.

Arrival Summary Overview

In Figure 5.13 summarises the main processes of all models and agents introduced previously, related to the arrival of buses in termini.

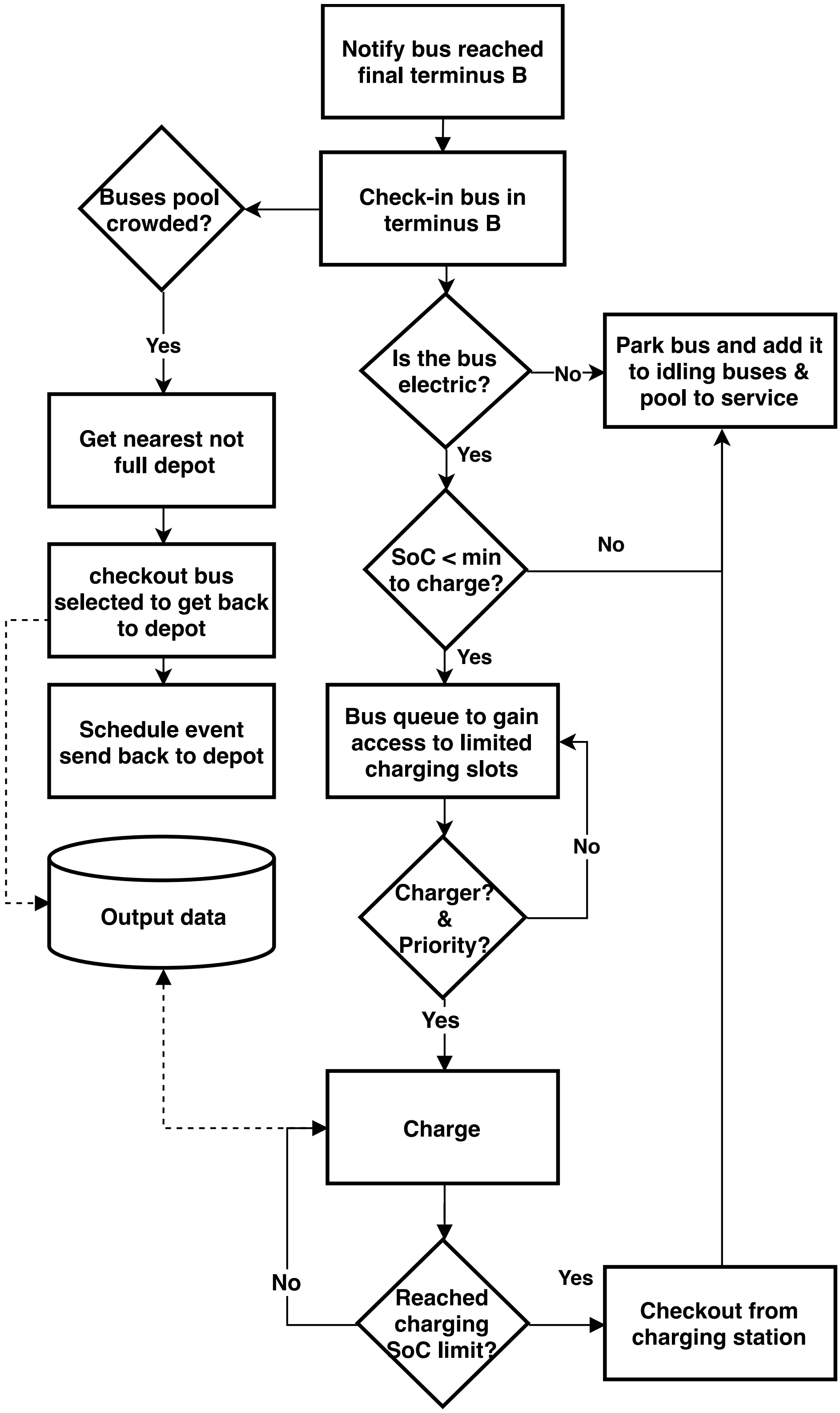


Figure 5.13: CityMoS simulation end and electric buses arriving flowchart simplified.

5.2 Model Configuration

5.2.1 Input Files

Although tuned and adapted to Singapore, the developed models can be exported and can simulated any other city in the world. Configuration files regroup the data fed to the simulation and describe specificities of the case study (city infrastructure and bus operations). In its actual state the simulation requires one main configuration file. This first layer aggregates all secondary configuration files and defines the parameters of the simulation such as the simulation start time, number of hours to simulate, number of cores to use, data to include in the output file. Most importantly, it includes the definition of all agents types.

On the second level, 4 files are required (related to bus operations). The first is the routing network. The second is the road network. Third is the bus schedule, defining all bus services to simulate, trips routes and directions. Fourth and final is the depot and termini models configuration file, defining the characteristics of the depots and termini simulated models. An overview of the different input configuration files is shown in Figure 5.14.

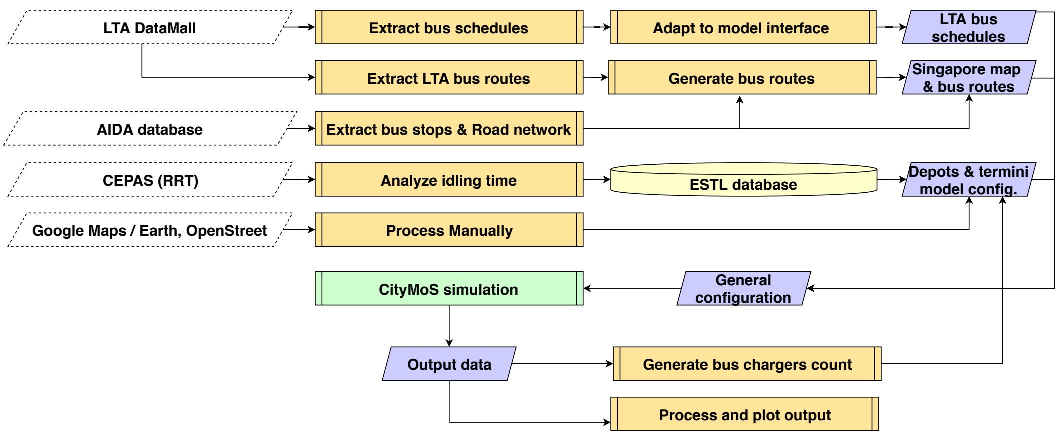


Figure 5.14: Toolchain and data pipelines overview.

5.2.2 Tool Chain

This section aims at connecting the previous Section 5.2.1 and Section 4.5. It intends to bridge the gab between raw data collected and ready formatted input files. In this master thesis, only one script was developed, while the rest of the scripts were only used according to the pipeline in Figure 5.14. The scripts are:

- "*Randomise bus routes*": before extracting LTA DataMall bus schedule, the first bus trips of all services started at the exact same time and had the same dispatch interval. To avoid this situation, a schedule randomisation patch was developed to distribute the start minute of each bus service inside its headway. Once the LTA schedule implemented, this was of no use any more.
- "*LTA bus service processing*" and "*schedule bus routes*": are used to extract bus schedules from LTA DataMall and to format them in the adequate structure to

meet CityMoS interface requirements.

- "*Output to PostgreSQL*": this script is used to upload simulations output to an ESTL PostgreSQL database.
- "*'Generate depots and termini*": this script takes a CityMoS simulation output file and calculates the number of chargers per charging station needed, according to a predefined usage cut-off threshold.
- "*Update depots and termini*": Once the "Generate depots and termini" script is run and number of chargers is determined, this script reads the depot and termini configuration file, updates its chargers count as well as the new aggregated power limit for each charging station.

5.3 Output Processing

5.3.1 Data Output Extraction

Periodic events are triggered every predefined time step at the start of the simulation. Triggered events are executed when a trigger in the code is reached.

Trigger data output events are to be positioned in the simulation source code in a way that is set off when the targeted information are still available. Details on agents are updated and deleted while the simulation is progressing to ensure memory optimisation. Data extraction time window is limited between the moment when the full data is available and when it is reinitialised or rewritten.

Different events had to be included, as every model had different characteristics and all data could not be mixed together or extracted at the same time. Both output event settings and content to be extracted can be defined in the general configuration file of the simulation. In this work, 6 data output events were added as shown in Table 5.3, to be able to collect the data summarised in Figure 5.15.

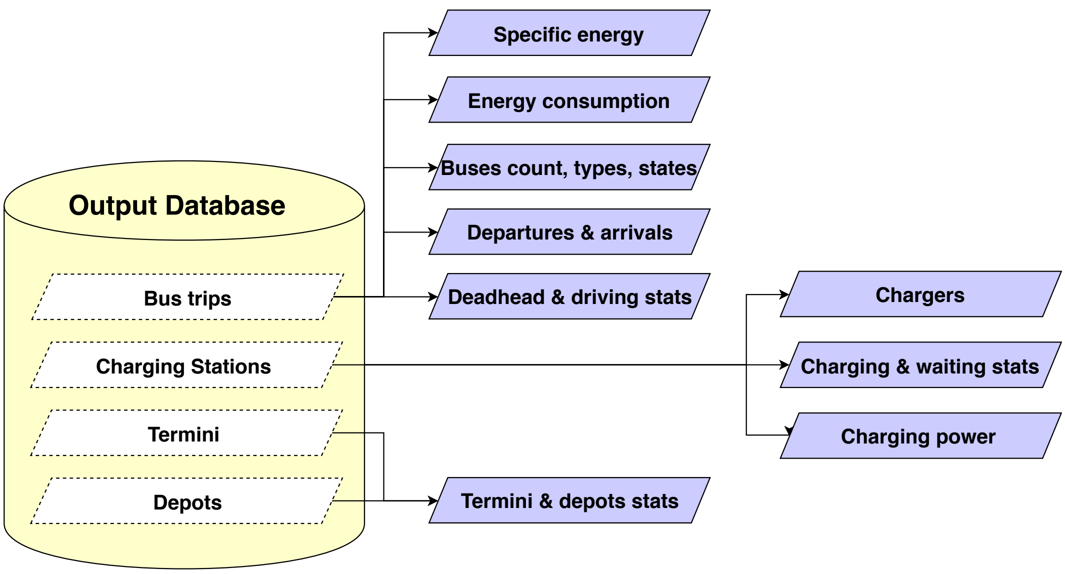


Figure 5.15: Output database content overview.

Table 5.3: Overview of data output events.

Event Scope	Event Type	Trigger	Content
Agent	Triggered	Agent created	Agents types parameters
Charging station	Periodic	10 seconds	Charging, waiting, power
Depot	Periodic	10 seconds	Capacity and buses flow
Terminus	Periodic	10 seconds	Capacity and buses flow
Non-Electric bus	Triggered	check-in/-out	Last trip details
Electric bus	Triggered	check-in/-out	energy, battery state

With the set output parameters, 50 MB of data was outputted for every simulated day. This number is highly depending on the configuration of the simulation. For the specific case of this work, simulating time was calculated to be two hours for one modelled operation day. All simulation results were limited to 5 days.

5.3.2 Results Processing

Output data was processed by a mix of SQL commands and Python code in a Jupyter notebook. First, a connection to the SQLite database was established.

```
# Most important libraries imported to process data output
import pandas
import matplotlib
import seaborn
import numpy

# Set connection to output database
import sqlite3
from pathlib import Path
sqlite_path = Path("../singapore/output/PW200_EL100_UT15_HSOC/
    citymos20181026083852.sqlite")
conn = sqlite3.connect(str(sqlite_path))
```

Listing 5.1: Set connection between Python notebook and SQLite database.

Then relevant data was filtered with SQLite commands.

```
sql_quiry_1 =
"""
    SELECT
        tripID,
        event_type,
        servicenumber
    FROM
        bus_trip
    WHERE
        servicenumber <> 'Off service'
"""
data_frame_1 = pd.read_sql(sql_quiry_1, conn)
```

Listing 5.2: Example of Python SQLite query used to filter out dead-heading trips from output data.

Results are shown in Chapter 6.

5.4 Calibration

The calibration process was initiated to ensure a bug free implementation and to reduce the divergence ratio from real-world. To do so, Singapore maps and networks were checked for errors and issues. Then, key parameters were adapted and tailored to ensure realistic results from the simulation, such as chargers count and dead-heading ratio.

5.4.1 Singapore Map and Bus Networks

Simulation output was compared to Singapore real-world data. City roads, depots, termini, and bus routes were assessed. Bus route lengths and driving time were also compared to key values from the previous analysis on the CEPAS dataset to minimise their error ratio and ensure the reliability of the simulation before the validation phase.

Singapore Map

To ease the debugging process, only a tiny section of the complete Singapore map was simulated during the development phase. The electric buses were first operated on few roads in the university town (UTown) in NUS campus with 2 bus services (D1, D2). Once the simulation stable enough, 3 fictitious bus routes were added (M1, M2, M3) to model more corner cases. Finally, a transition to Singapore map was initiated (see Figure 5.16).

Once the transition to the full map was done, various challenges rose. Deadlocks appeared after few hours of execution in the crowded streets of the city around big termini. The map had to be debugged and deadlocks solved. The map networks were corrected, adding more lanes to wrongly modelled roads, and in some case relocating slightly the depots and termini. A screen-shot of the original map before debugging, with buses deadlocks can be seen in Appendix A.2.

The dynamic dwelling model was also causing deadlocks in most of the bus stops at peak hours. Passengers waiting count at stations reached unrealistic numbers (more than 3000). For these reasons, the dynamic dwelling model was replaced by a fixed dwelling time of 5 seconds at all bus stops. This fixed value is unrealistic, but is implemented mainly as a workaround until the dynamic dwelling model is debugged.

Figure 5.16: Modelled map transition from UTown to full Singapore.

Depots and Termini Positions

In Figure 5.17, red dashed lines are showing the distance separating the actual location of depots and termini in Singapore map to the CityMoS modelled position. These structures are slightly diverging from their original positions, since the modelled Singapore map is not fully accurate. Some locations had to be adapted according to the map inconsistencies. Highest error rate is present in the limiting part between Singapore and Malaysia, as the neighbouring country was not modelled and the bus lines driving out of Singapore had to be aligned with this decision.

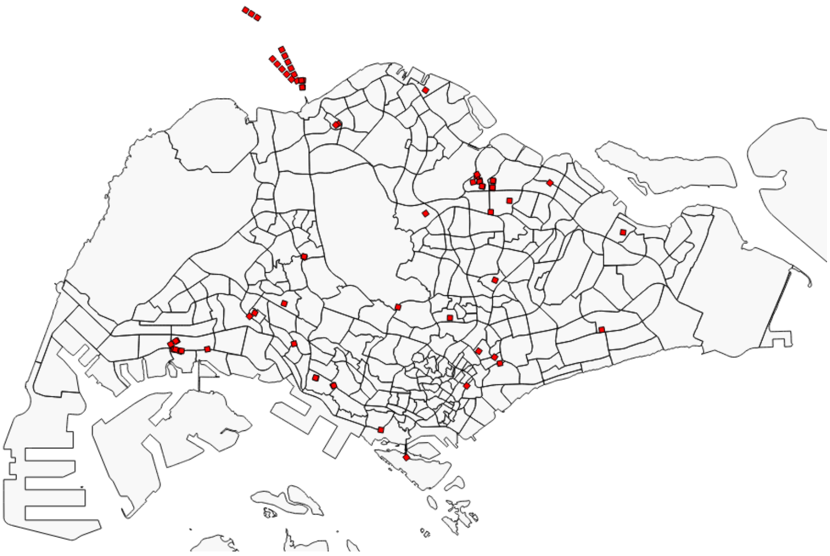


Figure 5.17: Distance between modelled termini/depots vs real-world location.

Bus Routes Length

Bus routes showed major issues, as more than 10 % of bus lines were 10 km longer than what they should have. The most inaccurate bus route was 70 km longer than expected.

After an iterative map debugging phase, the bus routes were consistent with reality to more than 95 % and only a maximum of 11 km longer route was noticed. Aggregated driven distances for all buses in Singapore per day is however corresponding to the one calculated from the CEPAS data set with values around 1,000,000 km.

Improvements achieved during debugging iterations are shown in Tables 5.4 and 5.5. The first table presents the decrease of bus routes longer by 1 km and 10 km than real-world. The second shows the decrease of routes length with 10 % and 100 % margin threshold.

Table 5.4: Results of the debug iterations in improving the bus routes.

Debug Iterations	1	2	3	4	5
> 1 km inaccuracy	228	234	218	208	186
< 1 km inaccuracy	263	258	247	285	307
> 10 km inaccuracy	54	57	53	21	3
< 10 km inaccuracy	437	435	412	472	490

Table 5.5: Results of the debug iterations in improving the bus routes.

Debug Iterations	1	2	3	4	5
inaccurate (10 % margin)	33%	35%	34%	29%	22%
accurate (10 % margin)	67%	65%	66%	71%	78%
inaccurate (100 % margin)	6%	7%	7%	1%	0%
accurate (100 % margin)	94%	93%	93%	99%	100%

Bus Driving Time

After the bus routes length calibration, driving time was analysed and compared to the real-world CEPAS data provided by LTA [52]. Figure 5.18 shows the distribution of driven distance per journey for CEPAS (on the top - red) and CityMoS output results (on the bottom - green). Given the dynamic characteristic of the developed simulation, modelled buses navigate in the map between bus stops according to Dijkstra algorithm, resulting in the minor divergence from the mileage reported in [14].

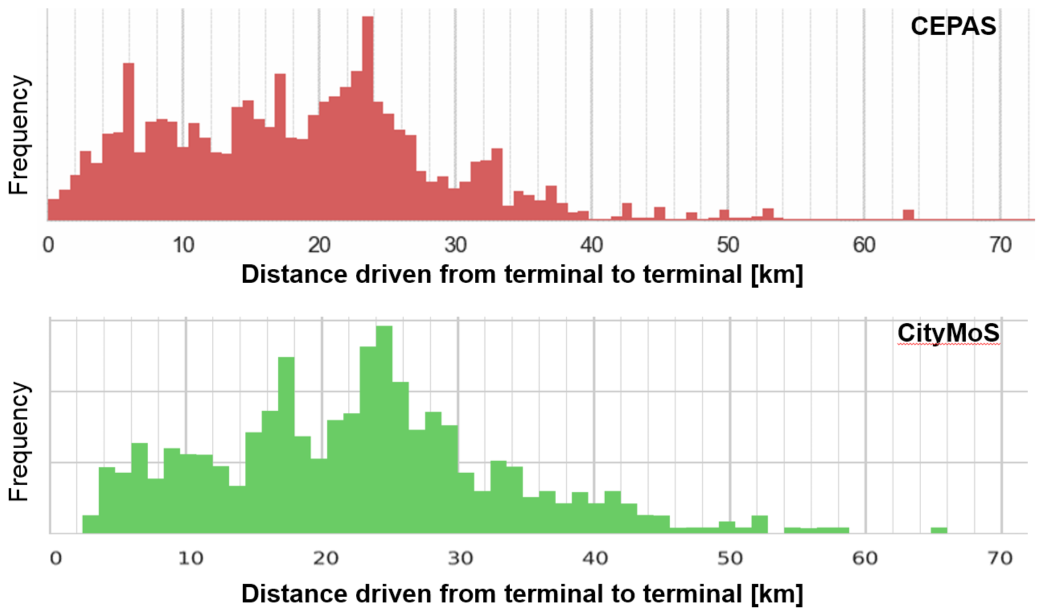


Figure 5.18: Distribution of driven distance per service from CEPAS dataset (top/red) and from CityMoS simulation results (bottom/green).

Bus Schedules

Dispatching was in the beginning of this work set to a fixed 10 minutes interval. As a second step, a randomisation was programmed to distribute the dispatching events and to avoid an overcrowded simulation. This implementation was used to finalise the tuning of the simulation and the debugging phase. However, implementing more realistic schedules was necessary.

To address this task, information on the bus services including start time of first and last bus, and headway for different times of the day were collected from LTA DataMall and were adapted to the input format of the simulation. The frequency of buses dispatch is assumed the same for before, during, and after morning peak and during and after evening peak. Finally, departure time is randomised at runtime inside the dispatch minute (0th to 59th second) to model a more realistic behaviour.

An overview of the number of bus departures per day is shown in Figure 5.19. The buses timetable shows two morning and evening frequency peaks. The morning peak reaches 600 buses dispatched over 5 minutes. During the day, the number is constant around 400 buses. Between 5 p.m. and 7 p.m. up to 500 bus departures are planned. The bus operation decrease starting from 9 p.m. and finish at midnight, except night buses.

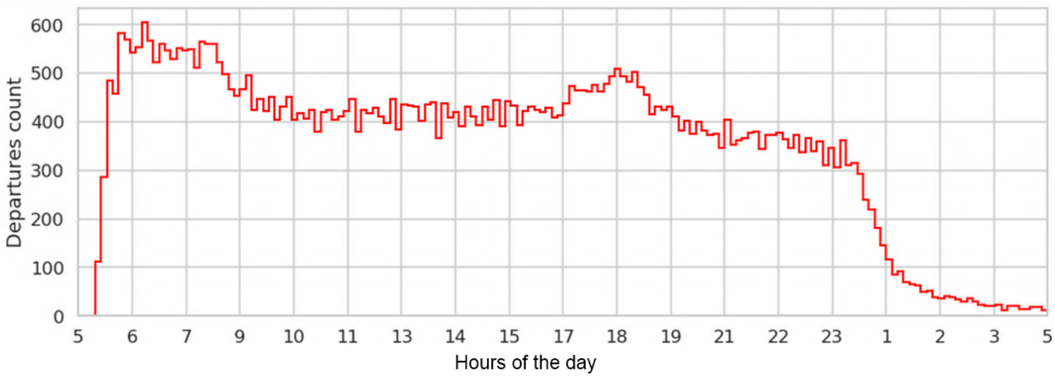


Figure 5.19: LTA bus scheduled departures for one operation day [52].

5.4.2 Chargers Count

The model was simulated in a way that if no bus is available before scheduled trip departure, it will be aborted. To enable the highest dispatching success possible and to ensure the initial requirements of simulating an electrification scenario with the nearest service reliability to real-world, the number of chargers need to be calibrated according to every simulated scenario.

A first step to calibrate chargers count, we assume that all parking slots in depots and termini are equipped with one charger (2472 chargers in total), resulting in the absence of queuing and waiting buses. After simulating a first time, the usage time of this unconstrained charging infrastructure was analysed and chargers showing a utilisation threshold (UT) under a chosen value were identified. Level of usage was calculated as the charging time divided by the total time. The chargers not used enough are considered superfluous. They are deleted and the depot and termini configuration file is updated. Finally, a new simulation is run with the updated parameters.

An overview of the first iteration of chargers calibration for the basic scenario (B0) defined in Section 6.1 can be found in Appendix A.4. The final number of chargers obtained after calibration per terminus and depot for B0 is shown in Appendix A.5.

5.4.3 Dead-Heading

The first executed simulations showed high dead-heading values, up to 60 %, which was too high (the only reference value found in the literature was 10 % [27] for two bus lines in Germany and Denmark). Unfortunately, no data was available on off-service mileage in Singapore. To decrease dead-heading between termini and depots, the process of selecting a suitable depots was improved by a scoring system.

The algorithm weights the distance between the terminus and the depot with 70 % (the nearer the location, the higher the score), availability of buses or available parking slots with 20 % and finally the size of the depot or terminus weight with 10 %, as shown in Equation 5.3. Availability refers to parking slots in the case of sending a bus back to depot or an available bus in the case of a call for refill in a terminus.

$$Score = 0.7 \cdot distance + 0.2 \cdot parking/bus\ availability + 0.1 \cdot structure\ size \quad (5.3)$$

5.5 Validation

Once all models were implemented and the simulation running, results need to be compared with reference works in order to validate the implemented models. In fact. minor errors in the models can have huge impact on the final results once scaled to a full bus network (snowball effect).

Given the size of the case study and in the absence of reference real-world data, validation is easier done aggregated over all the city and a bus-by-bus, line-by-line verification is more complex. Also, the developed models are based on various assumptions that are different from one work to another, making a direct comparison with the results obtained by other fellow researchers more complex.

5.5.1 Comparison with Benchmark Study

One of the remaining tasks was to assess the electrified models that have not been implemented yet in the real-world. This was done partly through comparing simulation output with values from previous work in Gallet et al. [14]. In this benchmark analysis, the aggregated energy consumed by buses in Singapore was studied. Results covered the daily energetic demand of 100 % electrification of buses in Singapore and its specific energy needs. Although data sources are similar in the two works, the adopted simulating approaches are totally different (see [14] for more details).

Gallet et al. [14] calculated a daily energy demand for on-service trips of 1.4 GWh in total for the full Singaporean public bus fleet, with an average specific energy of 1.6 kWh/km, 2.3 kWh/km and 2.5 kWh/km for single deckers, double deckers and articulated buses respectively. A comparison between the two results can be observed in Table 5.6. The simulation in CityMoS shows a lower specific energy consumption per km.

The data output of the CityMoS simulation showed an aggregated total energy demand varying from 1.4 GWh to 1.6 GWh per day depending on the parameters considered for the simulation with an average specific energy of 1.33 kWh/km and 1.91 kWh/km for single and double deckers respectively (20 % variation). This variation is justified by the over-simplified consumption model used in the current state of the simulation (powertrain, road characteristics, dwelling time, and traffic). A more accurate powertrain model based on realistic efficiency map is in the work at the time of writing.

The median value of total energy demand for a terminus-to-terminus journey was calculated, ranging between 19.8 kWh and 42.0 kWh, while in the reference work, it ranged from 28.7 kWh to 45 kWh, according to the service line.

The mean daily mileage of the buses was 220 km versus 186 km in the validation data and total energy demand per day was 330 kWh versus 336 kWh. Finally, 50 % of the bus routes required 40 kWh and 80 % of the bus routes demanded 60 kWh, equal to the results obtained in [14].

Table 5.6: Comparison of CityMoS simulation output versus reference work.

Parameters	**CityMoS**	**Gallet et al. [14]**
Buses mean daily mileage in Singapore [km]	220	186
Buses energy demand per day [kWh]	330	336
Energy required for 50% / 80% of services [kWh]	40 / 60	40 / 60
Aggregated daily energy consumption [MWh]	1433	1400
Median terminus-to-terminus energy [kWh]	30.9	36.8

5.5.2 Comparison with Scientific Literature

Results from the CityMoS simulation were compared to state-of-the-art literature, to assess the validity of the modelled assumptions. However, given the different case-studies, various parameters and assumptions made in each simulated electric public bus network system, most of the values can not be compared directly.

We selected the specific energy consumption as the comparison variable, so we can directly assess the obtained values. An overview of the specific Energy consumption from the scientific literature with sources can be found in Table 5.7.

Table 5.7: Electric bus specific energy consumption in the literature [12, 14].

Specific energy [kWh/km**]**	**Type**	**Source**
0.7	SD-10m	Vepsäläinen et al. [40]
0.9 – 1.14	SD-12m	Nurhadi et al. [77]
0.95 – 1.75	SD-12m	Lajunen [78]
1.05 – 1.26	SD-12m	Pihlatie et al. [6]
1.0 – 1.24 – 1.34	SD-12m	Aber [79]
1.2 – 1.5 (2.5 with heating)	SD-12m	Lindgren [80]
1.24 – 2.48	SD-12m	Zhou et al. [81]
1.34	SD-10/12m	Eudy et al. [82]
1.5	SD-12m	Electricity [83]
1.61 – 2.11	SD-12m	Gao et al. [11]
1.6 – 3.2 (2.3 kWh/km median)	DD-12m	Gallet et al. [14]
1.82 (6.67 MJ/km)	SD-12m	Mahmoud et al. [8]
2.1 – 3.4	AB-18m	Sinhuber et al. [84]
2.26 – 2.69 (2.47 kWh/km average)	AB-18m	Rogge et al. [85]
2.3	SD-12m	Goehlich et al. [86]

5.6 Parameters

Tables 5.9 and 5.8 regroup all variables related to electric buses operations and implemented in this master thesis, .

Additional variables were inherited from Singapore infrastructure models, traffic models, bus parent classes and other developed models in CityMoS, but they were not listed in the two overview tables. Variables not included, bus still relevant to the obtained results are battery related (efficiency, degradation, and weight), energy consumption related (forces and powertrain efficiency map).

Table 5.8: Parameters in CityMoS Simulation.

Parameter	Value	Location
Electric Buses		
Single Decker [% from total fleet]	70	Config.
Weight [kg]	12,500	.
Front area [m^2]	8.3	.
HVAC power [kW]	10	.
Battery capacity [kWh]	90	.
Double Decker [% from total fleet]	30	Config.
Weight [kg]	17,500	.
Front area [m^2]	10.35	.
HVAC power [kW]	15	.
Battery capacity [kWh]	150	.
Maximum number of buses available	5732	Config.
Electrification ratio [%]	25-100	Config.
Operations		
Fixed dwelling time [s]	5	Config.
Initial SOC [%]	100	Config.
SOC safety margin per journey [%]	50	S.Code
SOC minimum for off service trips [%]	15	S.Code
Minimum energy limit needed for trips [kWh]	30	S.Code
Dispatching & bus booking [strategy]	HSOC	Config.
Send back to depot bus selection [strategy]	LIFO	Config.
Send buses from depot selection [strategy]	HSOC	Config.
Extract bus from charging station [strategy]	HSOC	Config.
Depot/terminus scoring algorithm [%, distance, capacity, size]	70, 20, 10	S.Code
Depot / terminus selection algorithm [%, highest score, second, third]	93, 5, 2	S.Code
Depots/termini average idle buses [% capacity]	50	Config.
Planing time before departure [min]	15	S.Code
Time left to select bus before aborting trip [s]	30	S.Code

Table 5.9: Parameters in CityMoS Simulation.

Parameter	Value	Location
Charging		
Charging power [kW]	50-600	Config.
Electrified infrastructure (termini/depots) [%]	100	Config.
Maximum charging SOC [%]	90	S.Code
Charging station acceptance SOC limit [%]	90	S.Code
Critical lower SOC [%]	20	
SOC limit before decreasing charging power [%]	81	S.Code
Grid curtailing factor [%]	0	S.Code
Queuing		
Bus to promote from waiting to charging [Strategy]	RANDOM, HSOC, LSOC, FIFO, LIFO	Config.
Rebalancing		
Terminus full hard limit [% capacity]	100	S.Code
Terminus full soft limit [% capacity]	95	S.Code
Service Pool full limit [% capacity]	25	S.Code
Bus to exclude from pool if full [strategy]	FIFO	S.Code
Terminus needs refill [bus count per pool]	< 1	S.Code
Bus service full [% terminus capacity]	50	S.Code
Attempts to send bus back to depot	20	S.Code
Urgent check for bus to send back to depot time interval [s]	30	S.Code
Non urgent check for bus to send back to depot time interval (first check) [s]	240	S.Code
Non urgent check for bus to send back to depot time interval (second check) [s]	30	S.Code

5.7 Simulated Scenarios

70 scenarios were defined and simulated in CityMoS. An overview of all combinations included in this work can be found in Table 5.10.

Table 5.10: Overview of all simulated scenarios during the current work.

	Chargers Usage Cut-off Threshold			
Charging power [kW] - Electrification rate [%] - Queuing priority strategy	**- 0% -**	**- 10% -**	**- 15% -**	**- 20% -**
50 - 100 - HSOC	x			
100 - 100 - HSOC	x			
150 - 100 - HSOC/LSOC/FIFO/LIFO/RANDOM	x	x		B3
150 - 75 - HSOC	x	x		x
150 - 50 - HSOC	x	x		x
150 - 25 - HSOC	x	x		x
200 - 100 - HSOC	x	x	x	x
300 - 100 - HSOC	x	x		B2
300- 50 - HSOC	x	x		x
400 - 100 - HSOC	x	x	x	x
450 - 100 - HSOC/LSOC/FIFO/LIFO/RANDOM	x	x		B0-B1
450 - 75 - HSOC	x	x		x
450 - 50 - HSOC	x	x		x
450 - 25 - HSOC	x	x		x
600 - 100 - HSOC	x	x		x
600 - 50 - HSOC	x	x		x

6 Results and Discussion

70 scenarios were defined (see Table 5.10). All simulations were similarly parametrised, according to the Tables 5.9 and 5.8.

In contrast to most of the state-of-the-art studies that only study one operating day, we study the effects of cumulative days on the electric buses behaviours, range and availability. Although buses are fully charged upon initialisation at the start of the simulation, not all of them might able to fully recharge overnight over many operation days. Thus, buses may start the next day with a decreased range. This behaviour may cause a snowball effect that can be observed in some of the results presented below.

In this work, only four parameters were chosen. Their values were tuned to enable analysing their impact on the charging infrastructure , on the electric grid and the buses operations: the charging power, the public bus fleet electrification rate, the queueing to charging strategy, and the chargers cut-off threshold from the maximum charging slots that can be needed.

The simulations were run on a Dell Precision Tower 7910 server, with resources limited to one 3.1 GHz CPU and 128 GB of random access memory (RAM). It took between 6 h to 10 h to compute a full scenario. Due to the high amount of RAM needed, only two simulations could be run simultaneously.

6.1 Base Scenario (B0)

From the different simulated scenarios summarised in the Table 5.10, one was chosen to be the base scenario (B0). B0 is characterised by;

- 450 kW charging power: as the lowest standard charging power ([36]) ensuring stable operations with minimum chargers count.
- 100 % electrification: as the worst case in terms of infrastructure needs.
- Buses are prioritised when competing for charging according to FIFO logic: as the most intuitive strategy (absence of strategy).
- 20 % of usage threshold is set as the lower boundary to all chargers (a charger is excluded if condition not met): as a suitable value, after heuristic evaluation.

6.1.1 Electric Bus Count

The results show, that scenario B0 is perfectly feasible with 5391 buses. In 2013, Singapore counted around 4400 conventional buses. Thus, according to these results it is possible to replace a diesel-fuelled bus by 1.225 electric buses. Though, it is worth mentioning that the number of buses was not optimised in this work and so, this value may be reduced by decreasing the initial number of buses in the simulation. In this case, BEBs show an availability of 82 %, compared to non-electric vehicles.

6.1.2 Respect of Bus Schedule

With the pure electric bus fleet, it was possible to complete 47,458 bus journeys, which represents 99 % of all planned bus trips. 2275 departures were aborted, along the five simulated operation days. This is equivalent to 455 journeys missing per day, or 1.28 departure per service (both directions combined) per day.

A reason for these missed departures is the modelled terminus parameters such as size, initial bus count, and average idle bus count. These parameters are not yet calibrated with the reality. The missed departures were mostly located in the largest bus termini such as Woodland (46009), Yishun (59009), and Pasir Ris (77009) Bus Interchanges, as shown in Figure 6.1. The three termini alone are hosting 61 bus services, while the number of initial buses and average parked buses may be too low. For this reason, these termini are constantly empty and it results in aborted dispatches.

Analogous, the case of Soon Lee Bus Park (22609), starting location of 4 services, average idle bus count is set to 4 buses. In case all services dispatch events happen at the same time, the terminus will be empty. A call to refill the terminus with 4 new buses can take too much time, before the trip departure is aborted.

Missed departures count is a metric used to reflect of the inability of the simulation and its parameters to ensure the respect of the bus routes timetables.

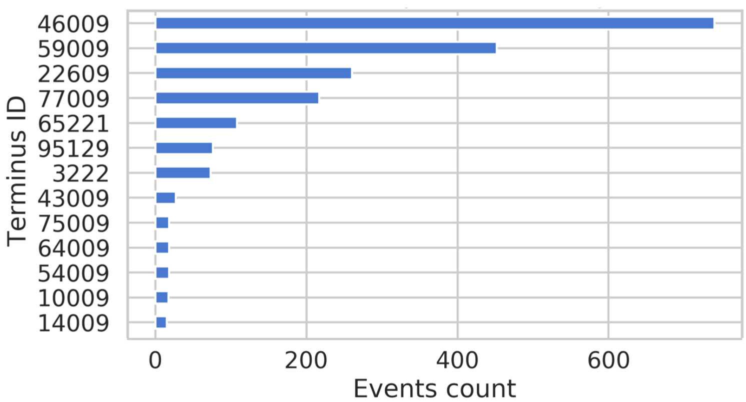


Figure 6.1: Overview of the missed departures count per terminus (5 days).

6.1.3 Statistics on Bus Trips

In this section, a detailed overview of the bus trips is given (on service). Off-service journeys were filtered out of these results and will be analysed later in 6.1.7. Results collected from the 5 operation days were averaged over 24 hours (from 5 a.m. to 5 a.m the next day).

In addition to the constant distance driven from terminal to terminal introduced previously in the validation Section 5.5, daily journeys count per bus, average trips length, duration, and summed driven distance per bus are presented.

Trips Count

Figure 6.2 shows the distribution of the number of trips per bus per day. According to the base scenario assumptions, every bus is driving on average 11 trips per day. Median is slightly above the mean, at around 11.5 service journeys daily. As no pressure on the number of buses was applied, nearly 20 % of buses drove less than 6 journeys per day, while some buses drove up to 30 journeys per day.

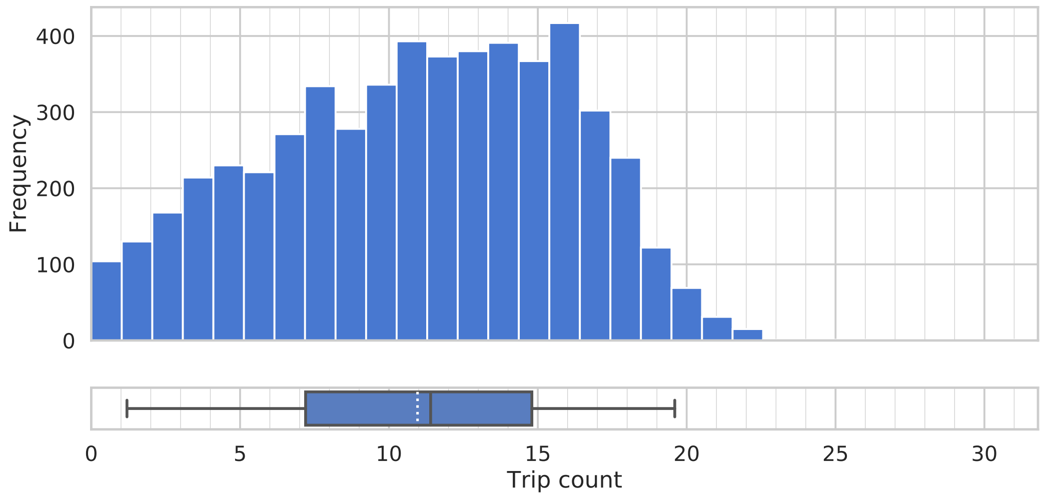


Figure 6.2: Distribution of Number of trips per Bus per Day. (Box plot whiskers set at 2nd and 98th percentiles.)

Length of Terminus-to-Terminus Trips

Figure 6.3 shows the distribution of average distance driven per bus per journey. Most buses drive in average between 10 km to 28 km per trip with a median of 20 km.

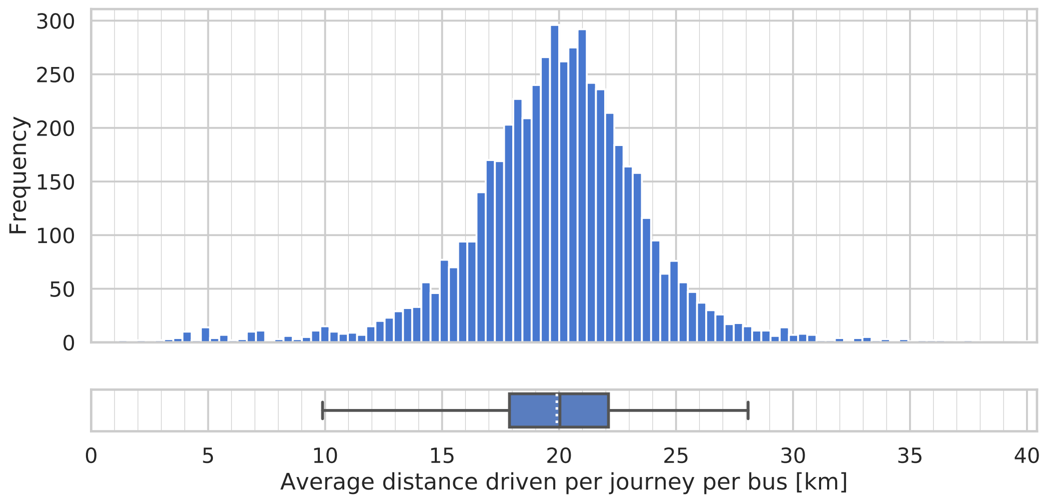


Figure 6.3: Distribution of the average driven distance per bus per journey. (Box plot whiskers set at 2nd and 98th percentiles.)

Duration of Terminus-to-Terminus Trips

Figure 6.4 presents the distribution of maximum journey duration per service. Terminus-to-terminus trip duration varies from the fastest, around 10 minutes, to the longest, around 2 hours. In average (also equal to median), a trip lasts 52 minutes.

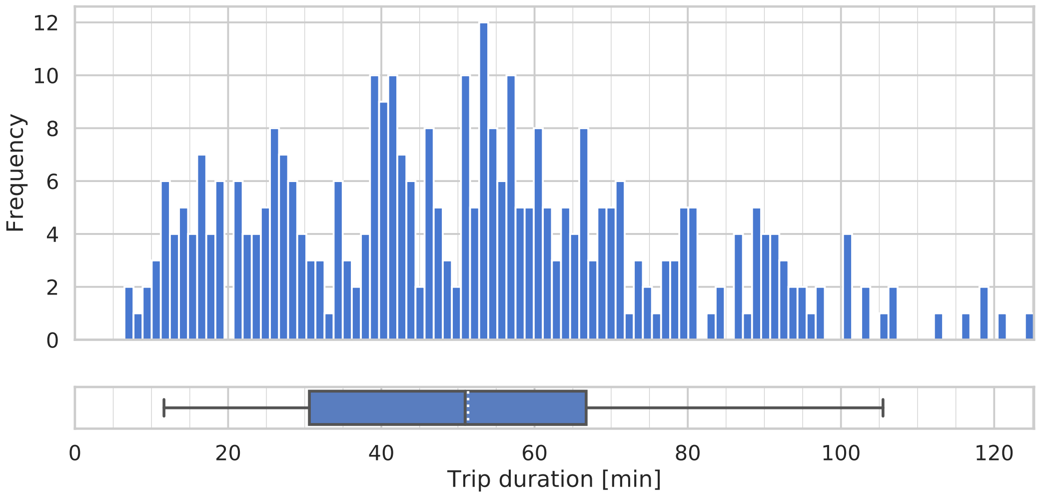


Figure 6.4: Distribution of the maximum trip duration per service. (Box plot whiskers set at 2nd and 98th percentiles.)

Daily Driven Distance per Bus

In figure 6.5, the distribution of daily driven distance per bus is shown. The values vary in our model from 20 km to 450 km, with a median value of 230 km.

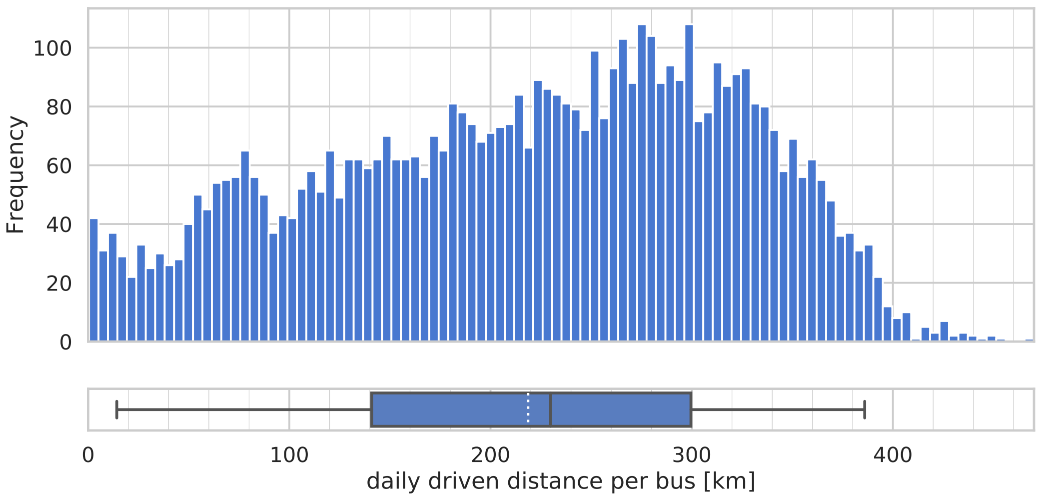


Figure 6.5: Distribution of the driven distance by buses daily. (Box plot whiskers set at 2nd and 98th percentiles.)

6.1.4 Electric Buses in Depots

Figure 6.6 shows the aggregated bus count over time in the 13 active depots in Singapore. Start point is the first day at 5 a.m. with an initial bus count of 80 % of total aggregated capacity.

The blue line represents the idling buses count. These buses are fully charged and are waiting to be dispatched. The red line represents the total buses count, which is the sum of idling and charging buses. The difference between the two lines for a given time represents then the aggregated charging buses count in depots.

The curves show 5 similar cycles according to the 5 simulated days (from 5 a.m. to 5 a.m. each). At the beginning of the cycle, buses are sent progressively out of the depots to support the network operations, as the dispatching frequency gets higher in termini at that time of the day (see Figure 5.19). This results in a major decrease in the number of buses in the depots, from 80 % to 40 %. The same number of buses will be sent back progressively to the depots at the end of the day, when bus departure frequency will decrease until the end of the daily schedule.

During the day, the whole network experiences two peaks (see Figure 5.19), in the morning and in the evening. During this time, departure frequency of buses in most bus routes increases and thus, more buses need to be injected in the network for a short period of time. Once the peak is over, the extra support buses are not needed any more and are sent back to their depots. This behaviour results in the two small depressions in the curve around 7 to 9 a.m. and 5 to 7 p.m..

Also, it can be observed that the red line is deviating more from the blue line after the first cycle/day. In contrast to the first day, when all buses were initialised with full batteries, buses seek more charging in the following days as some of them can not manage to get fully charged overnight.

Finally, given the lower limit of both lines at around 35 %, it can be concluded that buses are parked in the depots during the whole day and which are never dispatched. Thus, the number of buses created at the beginning of the simulation needs to be further tuned to eliminate superfluous buses and to ensure optimal number of vehicles.

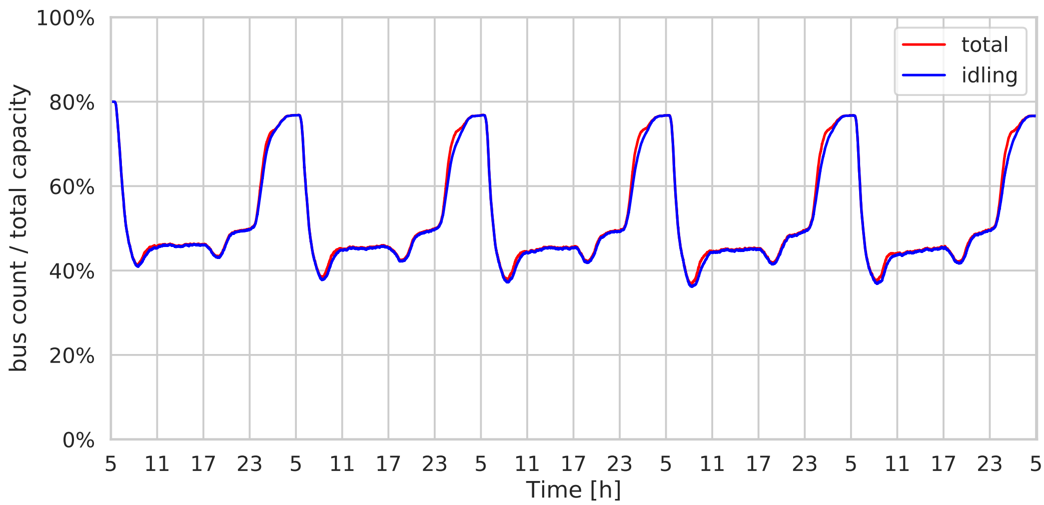


Figure 6.6: Overview of aggregated buses presence in depots over Singapore.

6.1.5 Electric Buses in Termini

Analogous to the previous section, Figure 6.7 presents the bus count sum over time in the 51 modelled termini in Singapore. The blue line represents the idling bus count while the red line shows the total bus count. The difference between the two lines for a given time represents the aggregated charging bus count in termini.

At the start of the daily operations, dispatch frequencies experience a rapid increase and buses are sent to ensure the service journey. This results in a major decrease in the number of buses in the termini (from 85 % to 30 %) proportional to the bus departure events increase (from 0 to 600 in less than an hour), as shown in Figure 5.19.

During the morning and evening peaks, termini experience a strong depletion in the number of bus count. This is influenced by the buses being dispatched from the depots to ensure a sustainable balancing. Once the day is over, the initial buses with the additional support buses are regrouped in termini, resulting in an higher bus count up to 85 %.

Given the fact that termini are the operative locations for bus trips and arrival stations for dispatched buses, their charging stations tend to experience more pressure and buses flow. In contrast to the depot overview in Figure 6.6, Figure 6.7 shows a clearer shift between idling and total buses count, caused by a high number of buses charging at the termini. This result is confirmed by the difference between the number of chargers needed in depots and termini. As shown in Figure A.4, termini require more chargers than depots.

Finally, the lower limit of both lines at around 30 % suggesrs that we still hold too many buses in some termini.

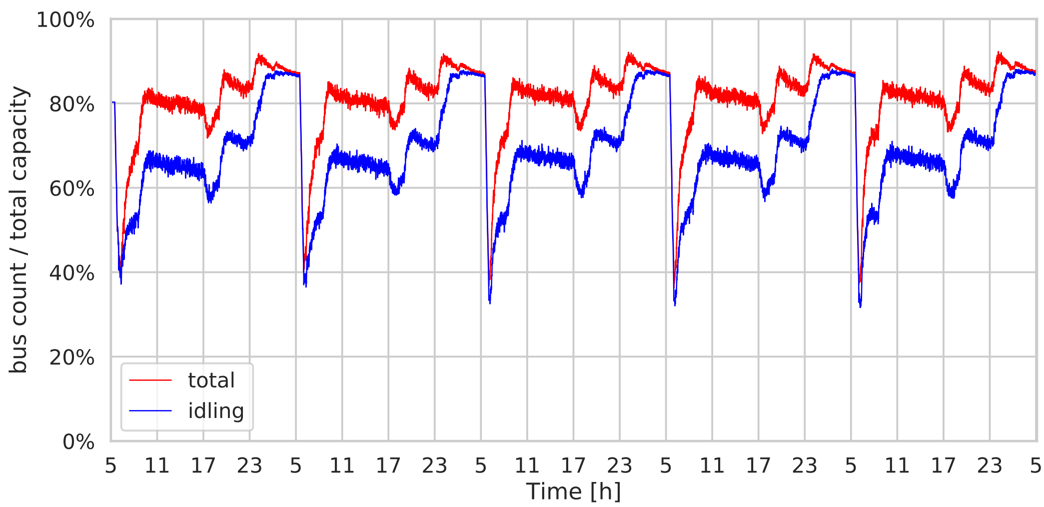


Figure 6.7: Overview of aggregated buses presence in termini over Singapore.

6.1.6 Electric Buses in Charging Stations

Figure 6.8 gives an overview of the buses flow in the charging stations in both depots and termini, aggregated to all Singapore. The blue line represents in this case the sum of all charging buses aggregated over 10 seconds time step. With the same vertical scale, the red line shows the number of buses waiting (queuing) at charging station.

From the figure, we notice that the number of charging buses goes up after operation start. Buses are initialised with full batteries and can operate without the need for charging. However, buses are modelled so that they will charge if their batteries are not full. After driving a full trip, they attempt to get an energy boost at every opportunity (instead of just idling). The charging buses count curve (blue) shows two peaks, slightly delayed after the schedule frequency peaks, as more buses are being dispatched during peak periods, and thus more buses partially depleted their batteries.

The red line peaks are the results of the pressure put on the charging infrastructure, as described in Section 5.4. The red line shows that buses are waiting for available chargers mostly after the morning peak and at the end of the operations. When all buses stop operating, they are all grouped at termini and are waiting to be fully charged overnight. An alternative would be to put more charging infrastructure at depots and to send the buses there, which unfortunately was not implemented yet.

If the number of chargers was unconstrained, as done in various state-of-the-art studies, buses would not have to wait, while competing for chargers is certainly a realistic behaviour. The impact of the successive simulation days can also be observed on the peaks magnitude. While waiting peaks reach only 60 and 110 in the first day, they reach 140 and 240 respectively after five days of operation. The charging buses count does not reach 0 between operation cycles, meaning that some buses are not fully charged before the start of the next day, leading to a slight snowball effect.

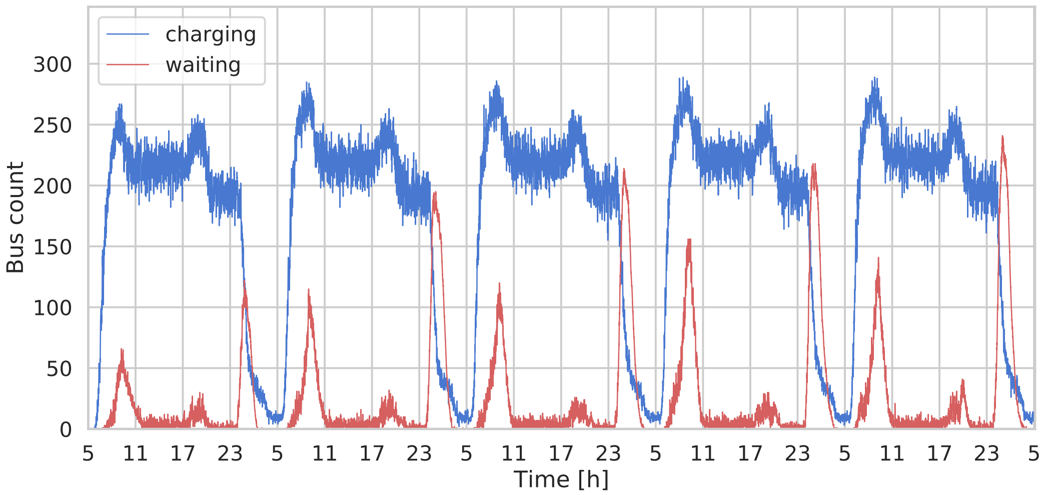
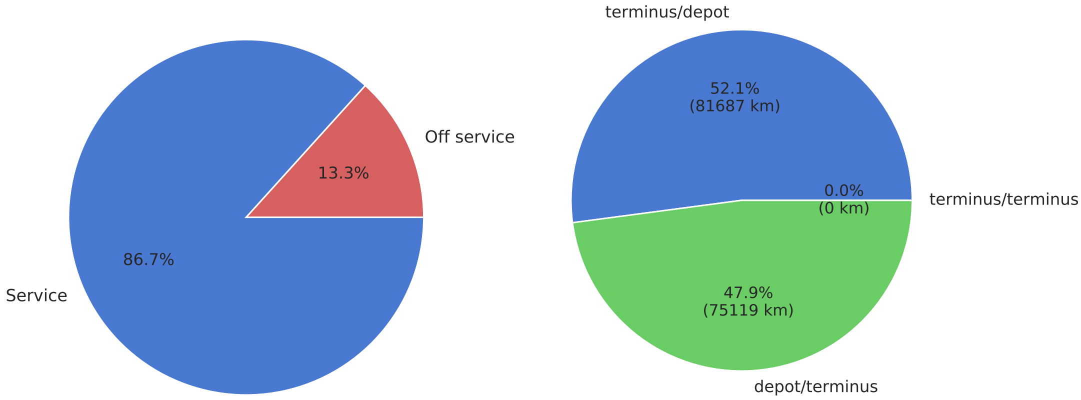


Figure 6.8: Overview of aggregated buses presence in charging stations.

6.1.7 Dead-Heading

The results in Figure 6.9 (a) show that for the base scenario, the off-service driven distance amounted to 13.3 % of the total driven distance in the simulation. This corresponds to 130 MWh consumed for non-service journeys, representing 8.2 % of the total energy consumption of the full public bus network. Figure 6.9 (b) shows that dead-heading trips from terminus to depot are responsible for 82,000 km off-service mileage per day for all Singapore, while 75,200 km is due to depot sending buses to termini as an answer to refill requests. Terminus-to-terminus trips are absent, as this rebalancing procedure was only implemented to be active in case of strong unbalancing between termini and depots, which did not occur in this simulation.



(a) Ratio on-service vs off-service (b) Detailed dead-heading distance

Figure 6.9: Overview of dead-heading driven distance for B0 scenario.

6.1.8 Charging Power

Focusing on one operation day for the entire electric public bus network results in the aggregated charging power demand presented in Figure 6.10. The red line shows the instantaneous power demand over 10 seconds average. The blue line represents the 5 minutes moving average of the power demand. The red line shows high fluctuations as buses charge in few minutes and result in rapid variation of number of charging vehicles. This variation is also explained by the fact that each charging start or stop incurs a fluctuation of the aggregated charging power of up to 450 kW.

During off-peak hours, the charging infrastructure requires between 80 MW to 100 MW, while it reaches 115 MW peak around 9 a.m. All queuing buses finish charging few hours after service end and the charging curve tend toward zero. However, it never reaches the zero line, as not all waiting buses have enough time to fully charge overnight.

Further analysis of a single charging stations demand shows a median value of 5.75 MW. Also, 95 % of the charging stations require at most 8 MW.

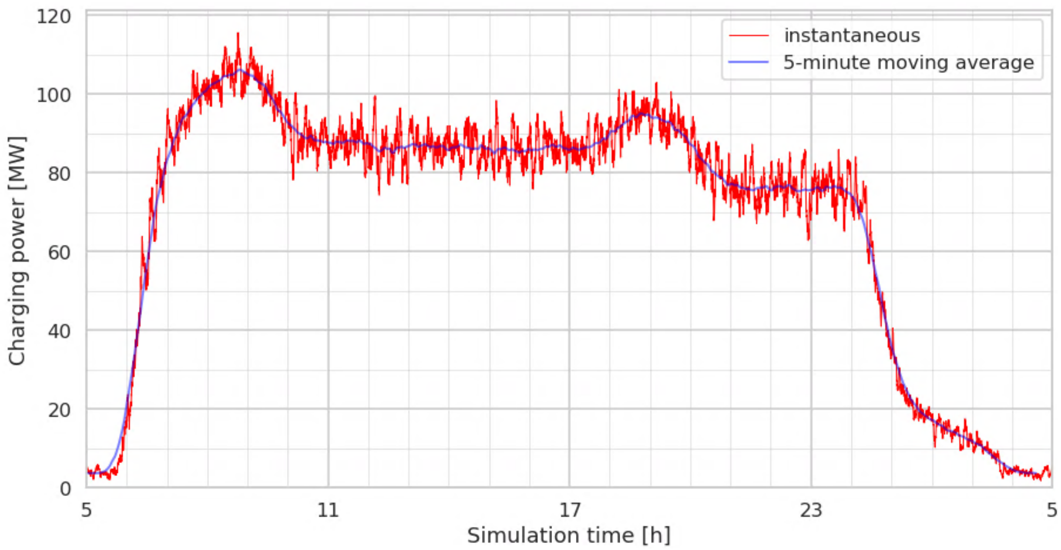


Figure 6.10: Charging power for electric buses aggregated over Singapore.

Figure 6.11 shows the cumulative distribution of charging power demand over time. The results show that with 120 MW power installed and for the assumptions made for B0 case, a full electrification is eventually feasible from an energetic point of view. With 100 MW charging power available, it would be possible to cover the power demand of all charging stations in Singapore 90 % of the time.

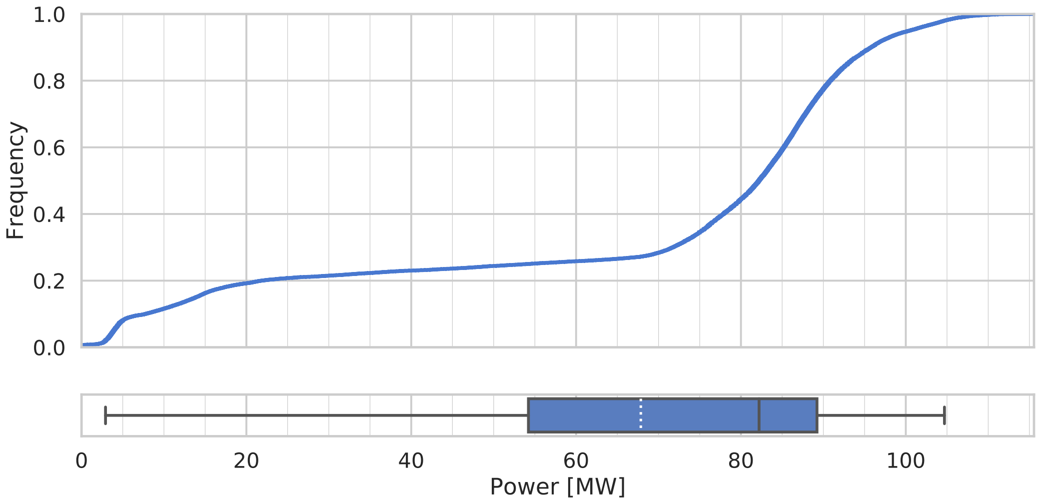


Figure 6.11: Cumulative distribution of charging power demand over time. (Box plot whiskers set at 2nd and 98th percentiles.)

The fluctuations of the charging power becomes higher when the charging power demand of only one charging station is shown (see Figure 6.12).

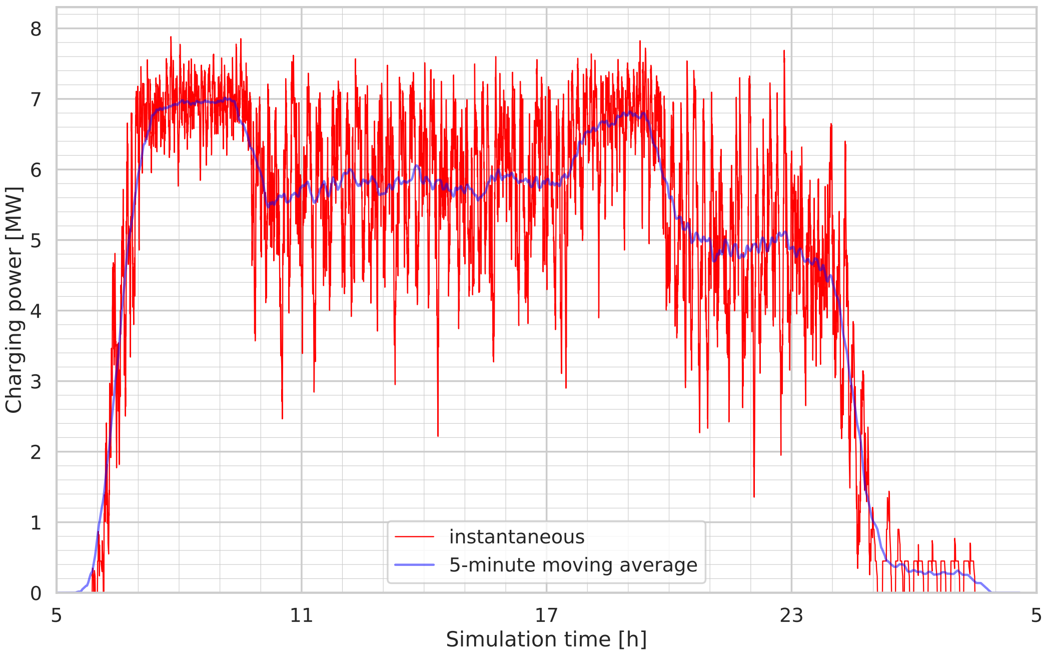


Figure 6.12: Charging power for electric buses at Boon Lay.

When the size of the charging station is even smaller, the variations are very important compared to the total installed capacity (see Figure 6.13).

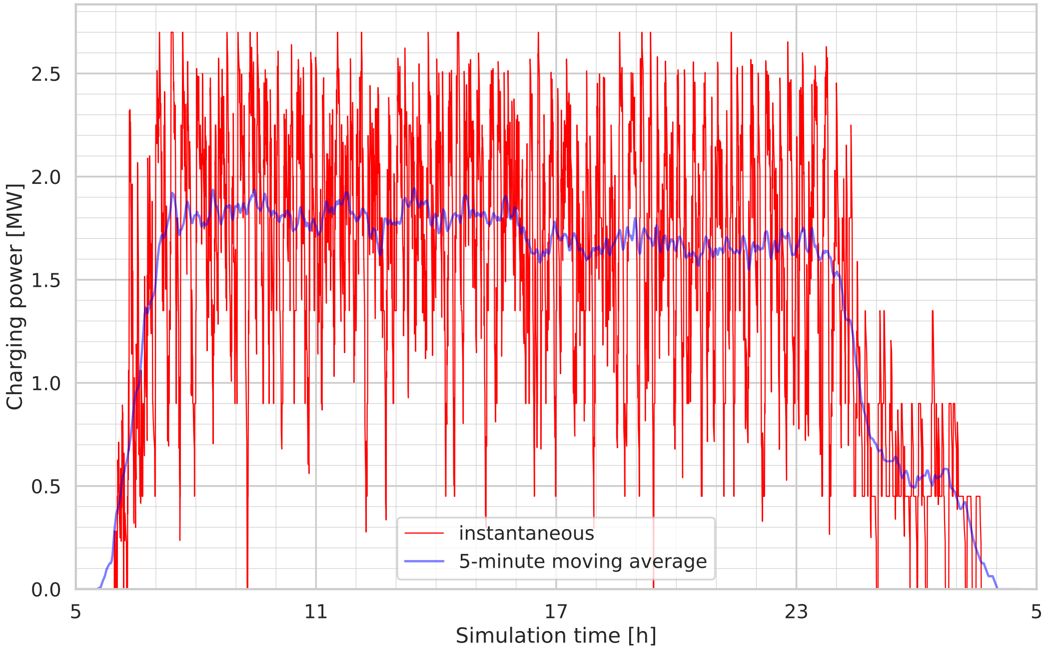


Figure 6.13: Charging power for electric buses at Eunos.

6.1.9 Charging Infrastructure

After the calibration phase,the number of chargers was calibrated to obtain 20 % minimum usage threshold per charging slot. The total number of chargers aggregated over all charging stations was equal to 330, distributed as presented in Annex A.5.

For example, Figure 6.14 shows the level of usage of the chargers installed at Woodlands interchange. As this graph represents the results after the calibration process, no chargers are showing a usage level under 20 %.

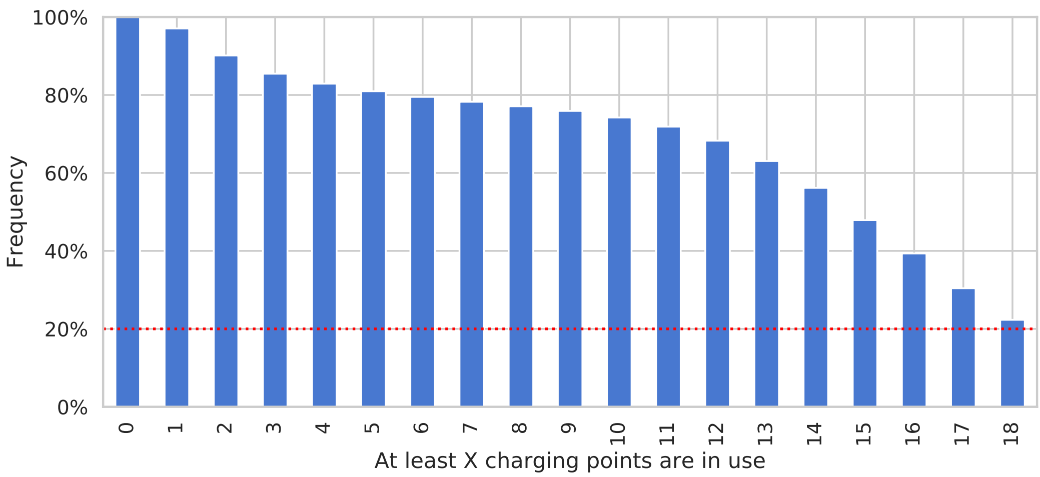


Figure 6.14: Overview of the chargers usage in Woodlands Interchange terminus.

Figure 6.15 gives an overview of the number of available chargers aggregated over all Singapore over the five simulated days. Analogous to the previous results, the free chargers count variations are following the scheduling cycles from 5 a.m. to 5 a.m. of the following day. Chargers are used during the day, where buses charge between trips. The impact of the two operation peaks is causing a depression in the number of available chargers, mirroring the charging power curve in Figure A.5.

Interestingly, while it can be seen in Figure 6.8 that the number of buses queuing for charging is high around midnight (with nearly 250 buses waiting), in Figure 6.15 the number of available charging slots is high at that time. This apparent contradiction can be explained by the fact that the waiting buses are concentrated in few charging stations where the number of chargers is not sufficient to deal with the long waiting queue, while the rest of the charging stations are able to process their queue and thus reach quickly a state where a lot of charging slots are free. This problem could be resolved in the future by rebalancing waiting uses to nearby charging station with sufficient free capacity.

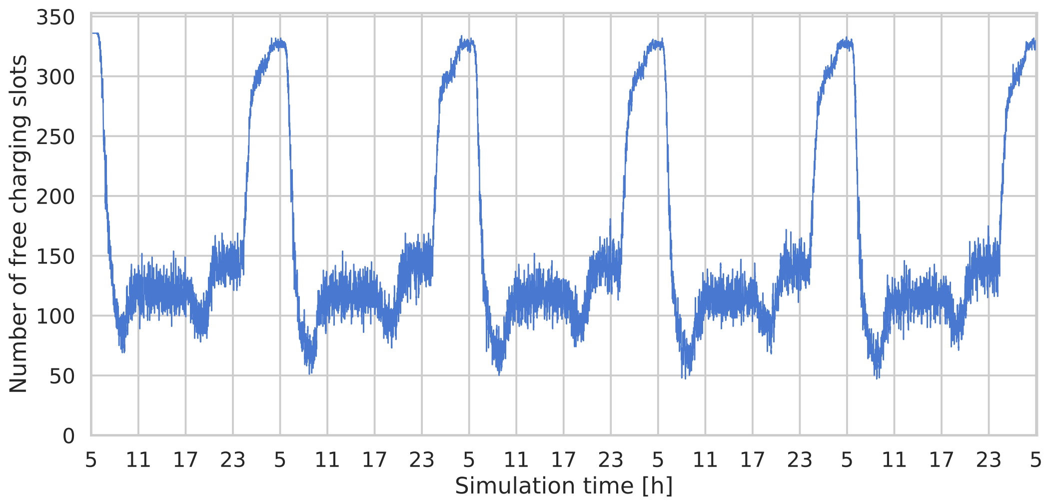


Figure 6.15: Number of free charging slots aggregated over all Singapore.

6.1.10 Energy Demand

Figure 6.16 gives an overview of the energy consumed per terminus-to-terminus journey and per service, regardless of buses types. The best case scenario per service with the lowest energy consumption registered during the simulation is shown in green. The average case scenario with the mean consumption is shown in blue and the worst case, were maximum values of the energy consumption per service were considered is represented in red.

Considering the most optimistic energy consumption values, most bus services consume from 5 kWh to 50 kWh, with a median of 20 kWh. In average, most bus services consume from 7 kWh to 70 kWh, with a median of 30 kWh. Given the worst case scenario, values vary from 10 kWh to 95 kWh, with a median of 46 kWh

Figure 6.17 shows the distribution of all service journeys for the two bus types implemented: single deckers (SD) in blue and double deckers (DD) in red. The results show also that SDs consume less energy than DDs , with a energy demand varying between 5 kWh and 80 kWh per trip. The SD energy demand median is around 25 kWh, and 80 % of the buses consume less than 35 kWh per trip. DDs consume between 7 kWh and 115 kWh per trip. The median is around 40 kWh, and 80 % of the buses require less than 60 kWh.

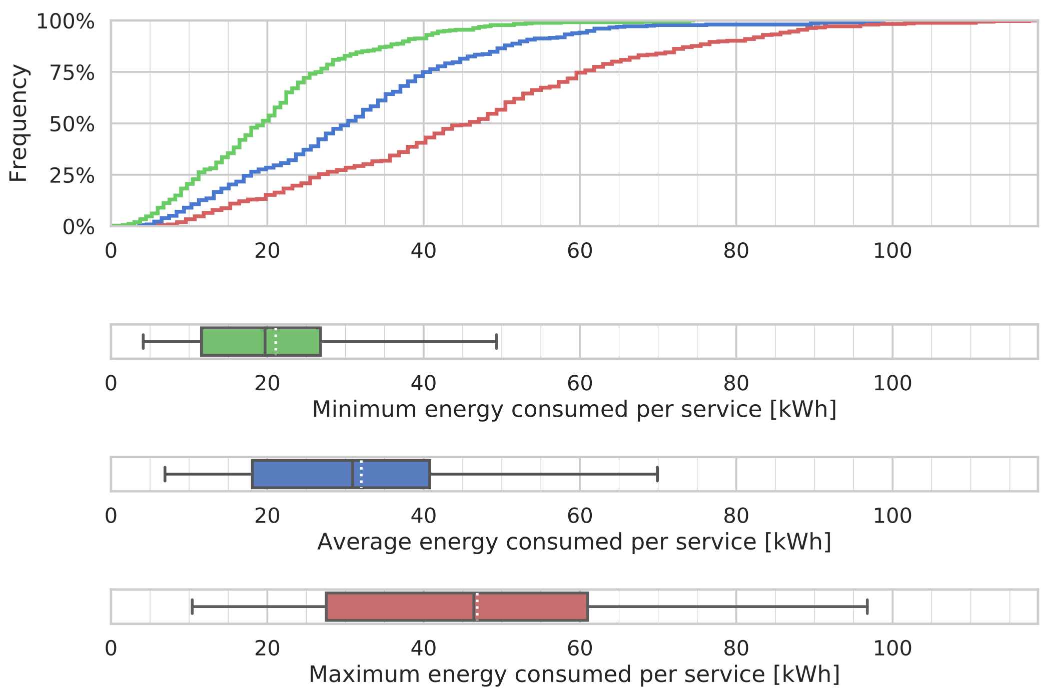


Figure 6.16: Cumulative distribution of the best, average, and worst energy demand per journey and service. (Whiskers set at 2nd and 98th percentiles.)

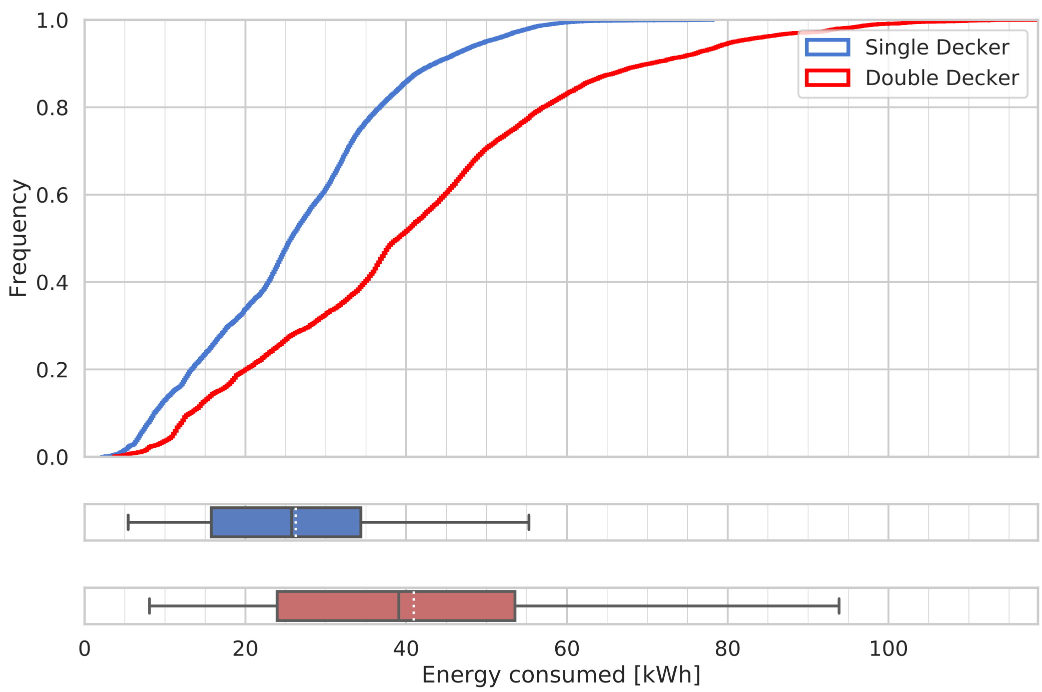


Figure 6.17: Cumulative distribution of energy demand per journey per bus type. (Box plot whiskers set at 2nd and 98th percentiles.)

Analogous to the previous results, Figure 6.18 shows the cumulative distribution of the daily energy demand per bus for service trips for both single decker (blue) and double decker buses (red) respectively. SDs daily energy demand ranges from 10 kWh to

525 kWh, with the median at nearly 340 kWh. DDs range between 20 kWh and 760 kWh, with a median value at around 460 kWh.

Figure 6.19 gives an overview of the state of charge (SOC) consumed per trip in relation to the driven distance for both electric bus types (service and off-service trips). A linear relationship can be observed. The slope is however different for different service type and bus characteristics. The difference between SD and DD SOC consumption per driven distance is caused by the different characteristics of the buses such as the weight and the battery capacity. Off service trips on the other hand are not subject to dwelling, so trips are faster and end up requiring less energy for the same distance.

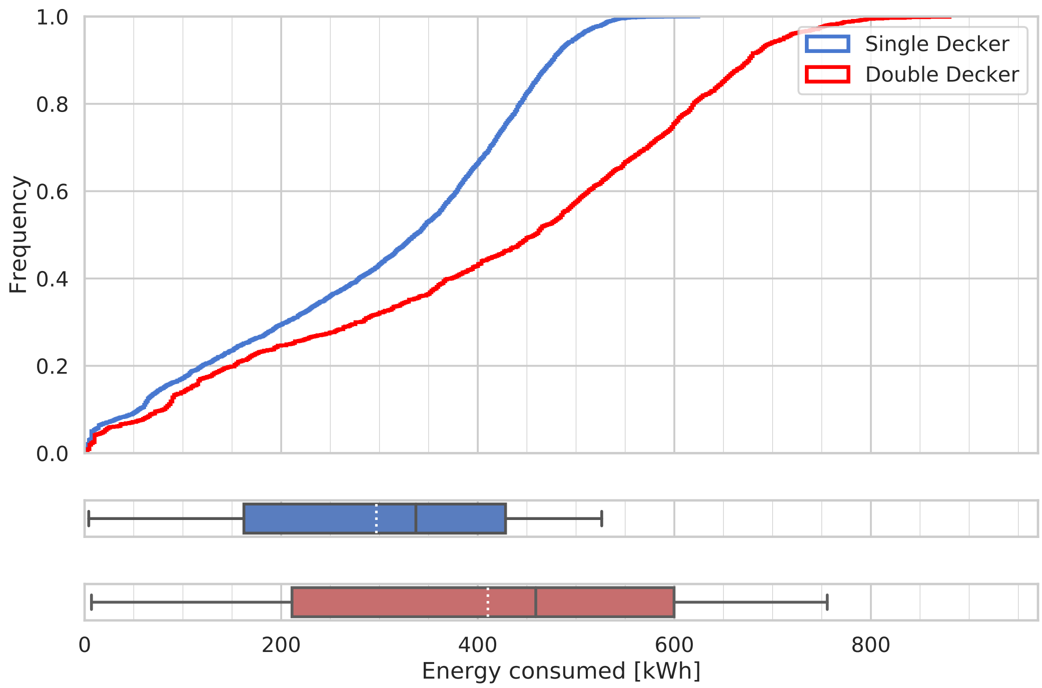


Figure 6.18: Cumulative distribution of daily energy demand consumed per bus type. (Box plot whiskers set at 2nd and 98th percentiles.)

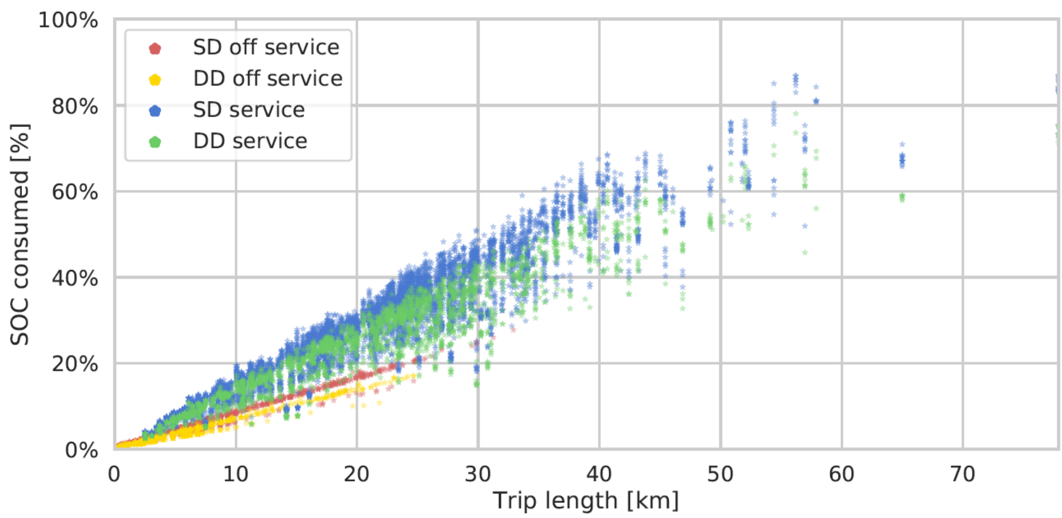


Figure 6.19: State of charge consumed by single and double decker buses in function of the trip length. (for both on and off-service journeys.)

6.1.11 Specific Energy Consumption

Figure 6.20 shows the distribution of the specific energy demand categorised by vehicle type (SD (blue) and DD (red)). Values consumption are mainly due to the specificities of the driven routes and routes conditions. SDs specific energy demand ranges from 1 kWh/km to 1.6 kWh/km, with a median value of 1.3 kWh/km. DDs specific energy demand varies between 1.4 kWh/km to 2.3 kWh/km, with a median value of 1.9 kWh/km. The values correspond to the ranges given in the scientific literature (see Table 5.7).

The values obtained in this work were considered to be too optimistic as the powertrain model implemented was simplified and no passenger weight was taken into account.

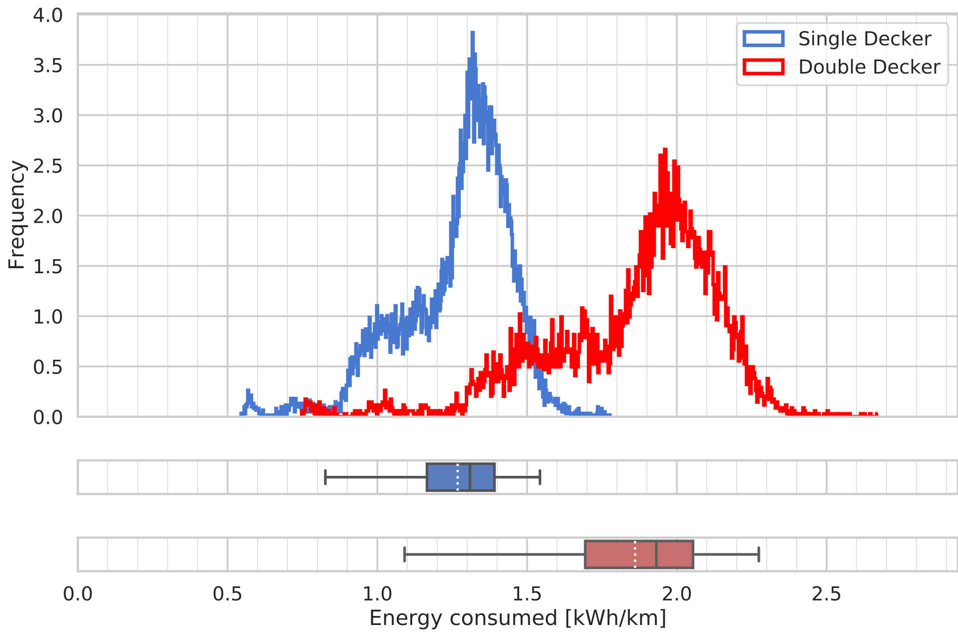


Figure 6.20: Distribution of the specific energy demand of single and double deckers.

Analogous to the previous results, Figure 6.21 represents the specific energy of different bus types in relationship to the distance of a terminus-to-terminus journey.

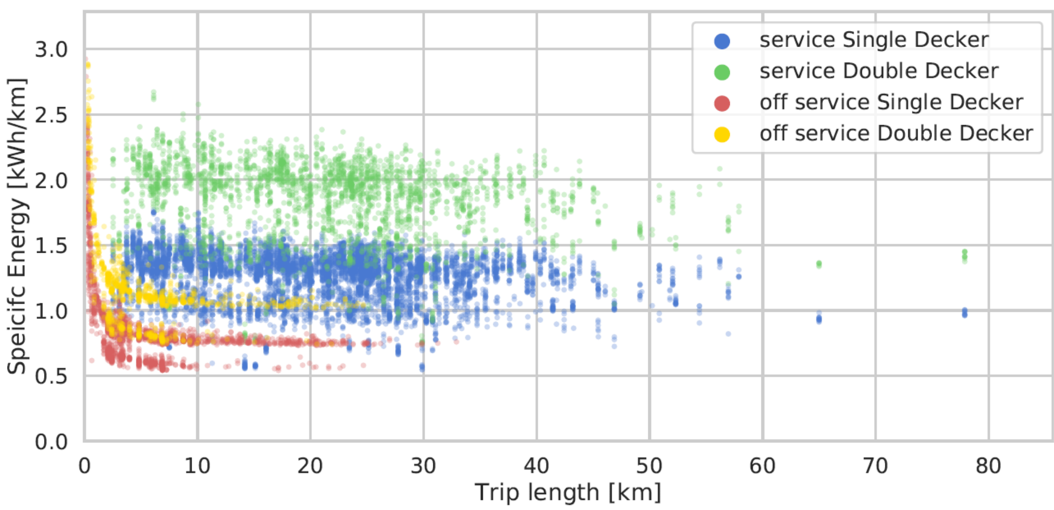


Figure 6.21: Specific energy of single and double decker buses per trip length.

6.2 Scenario Comparison

An overview of the results of all scenarios can be found in the Table A.1. In this section, observations from the various simulated scenarios are presented. The four tuned variables are the following: "*Nominal charging power (CP)*" is defining the highest available power at every charger. "*Utilisation threshold (UT)*" represents the lowest usage level (charging time/simulation time) under which a charger is considered superfluous. "*Electrification level (EL)*" is defining the ratio of electric buses of the total bus fleet. "*Queue prioritisation strategy*" defines the strategy used to prioritise queuing buses.

6.2.1 Charger Nominal Power

In this subsection, four scenarios are compared. All analysed cases have a 100 % electrification level, 20 % usage threshold and waiting buses are prioritised according to the HSOC strategy. Chargers nominal power is tuned: 450 kW (scenario B1), 300 kW (scenario B2), and 150 kW (scenario B3).

Chargers Count

The obtained results show that a higher charging power is directly proportional to the decrease of the number of required chargers for a given utilisation threshold. B1 scenario was simulated with 333 chargers while scenario B2 needed 420 chargers and scenario B3 used 872 charging slots.

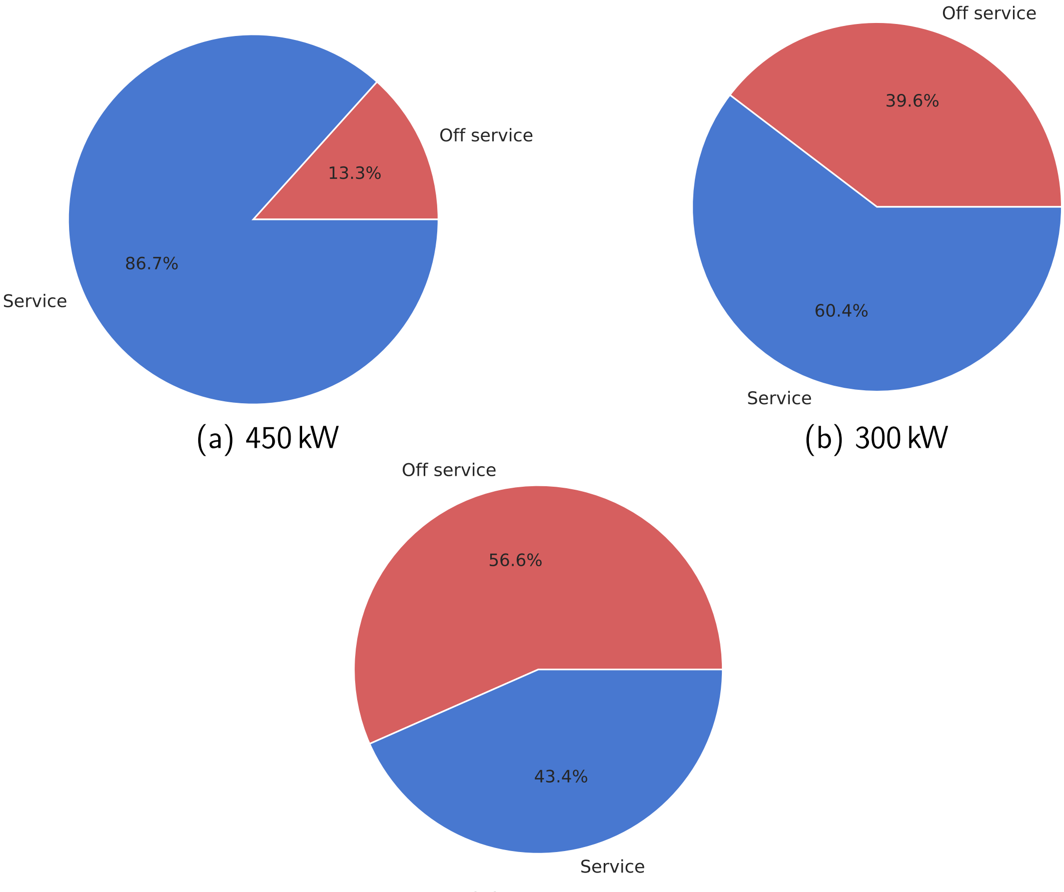
Dead-Heading

Figure 6.22 mirrors the relation between charging power and dead-heading distance. In scenario B1, the off-service mileage represented 13.3 % of total driven distance, with an energy consumption of 25.6 MWh. In scenario B2, buses drove 40 % off-service and consumed 96 MWh. Scenario B3, characterised by the lowest chargers power, presents the highest dead-heading ratio of 56.6 %, and a 112 MWh dead-heading consumption.

A first assumption can be stated that increasing the charger nominal power is decreasing the dead-heading distance and the related energy consumption. However, results show that this trend is only valid for nominal charging power under 400 kW. From the rest of the results shown in Table A.1, we notice that a 600 kW charging nominal power reduces the dead-heading to only 12 % with dead-heading energy consumption of 23.2 MWh.

Missed Dispatch Events

From the Table A.1, we can observe that increasing chargers nominal power reduces the sum of missed bus journeys during the whole simulation. Aggregated over the 5 simulated days, scenario B1 missed count is 2179. Scenario B2 and scenario B3 result in 14,203 and 26,668 missed trips respectively. However, this trend is only observable for chargers nominal power under 400 kW. For higher values, the gain is minimal. This can be explained by the slow charging pace, resulting in the unavailability of buses for a longer time. This is more accentuated through the operation days.



(a) 450 kW (b) 300 kW (c) 150 kW

Figure 6.22: Ratio of driven distance on service versus off service.

Power Demand

As shown in Figure 6.25, with 150 kW charger nominal power, the aggregated charging power demand presents less fluctuations than with 300 kW (Figure 6.24) and with 450 kW (Figure 6.23). Comparing the three graphs to analyse the daily charging power demand with ultra-fast and slower charging shows that decreasing charging power does not decrease the overall power demand (see also Figure A.6 and Figure A.7). The contrary can actually be observed from the graphs, where impact of the cumulative discharge of the buses can be observed. Scenarios B1, B2, and B3 present a peak of 113 MW, 119 MW, and 126 MW respectively. To cope with the slow charging pace, more charging points are needed to enable the same bus fleet to respect the dispatching schedule and thus, it results in an equal or higher charging power demand. A compromise has to be achieved when choosing the chargers nominal power. The aim is to enable a steadier charging power curve, while ensuring a low and constant charging demand.

After days of operation, the charging curve for low nominal power reaches a saturation level, where the peak power demand is constant at more than 90 % of the aggregated nominal charging power available at charging stations. This can be observed starting from day 3 in scenario B3 at 120 MW. Small decreases are also present during the day, that are caused by the dispatch of buses from the charging stations at peak hours. Figures A.8 and A.9 show the aggregated charging power demand for another set of 3 scenarios where the number of chargers is the same regardless of the charging power.

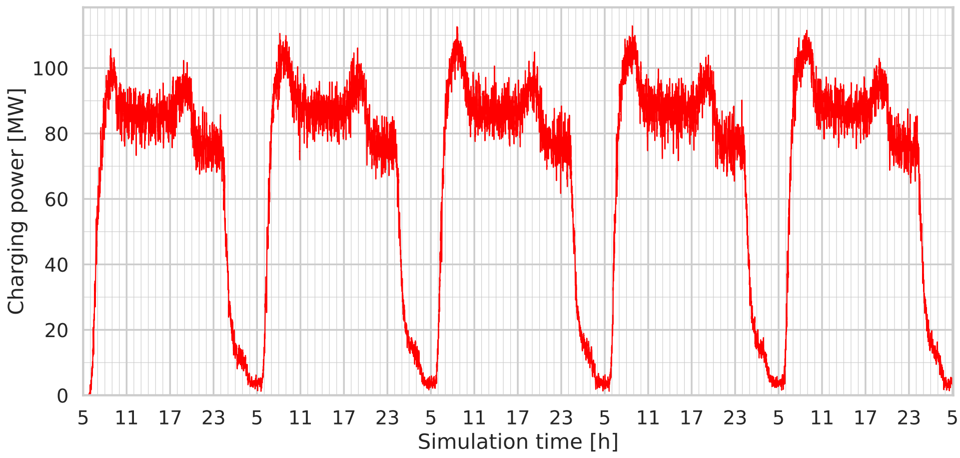


Figure 6.23: Power demand for electric buses aggregated over Singapore for 450 kW charger nominal power.

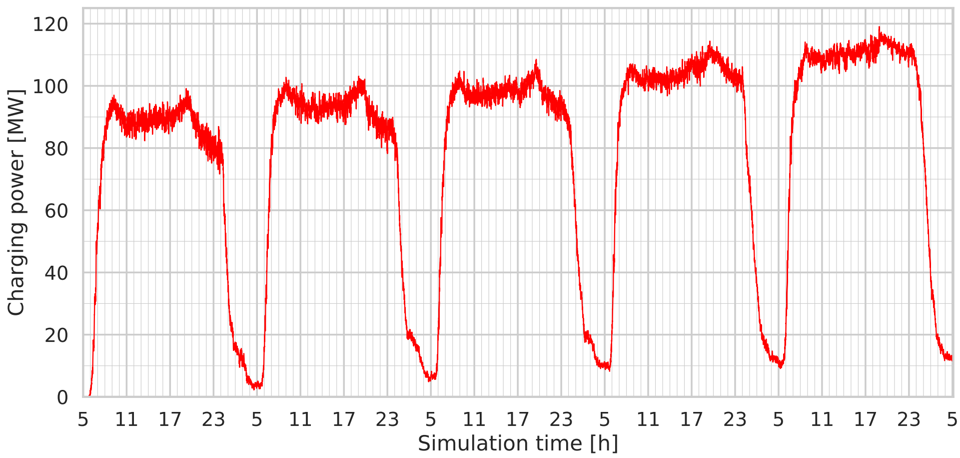


Figure 6.24: Power demand for electric buses aggregated over Singapore for 300 kW charger nominal power.

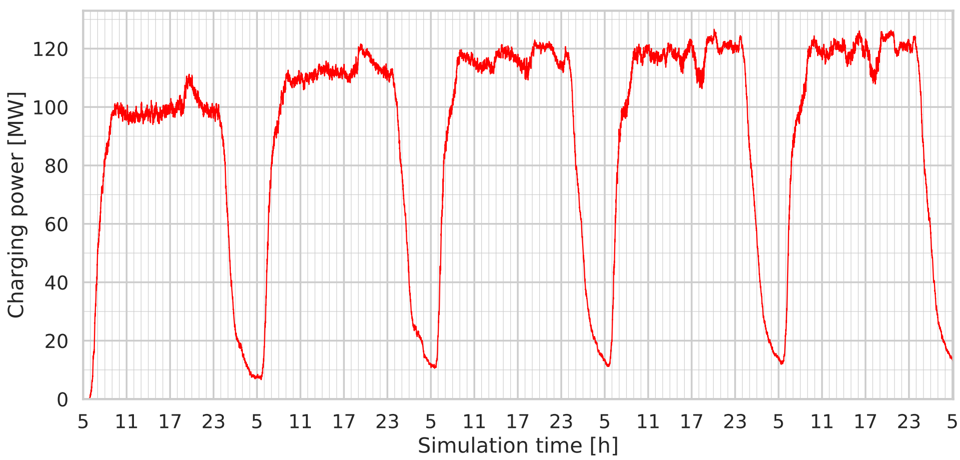


Figure 6.25: Power demand for electric buses aggregated over Singapore for 150 kW charger nominal power.

Charging Station Bus Count

Comparing Figures 6.26, 6.27, and 6.28 shows the impact of the nominal power of the chargers over the whole electric buses operations. For scenarios B1, the daily cycles are stable and the impact of successive days is only slightly noticeable on the waiting buses count. From the 333 available chargers, only a maximum of 280 are used simultaneously. The charging buses curve follows the bus service schedule, with daily peaks corresponding to the traffic peaks and a minimum at the end of the day.

In contrast, for scenario B2 and B3 the simulation is getting unbalanced along the operation days. As all chargers are busy during the daily operation, the fifth day the number of waiting buses is increasing to reach more than 2000 during the day and 3500 during the night. This represents respectively 37 % and 65 % of all buses.

From the figures, it can be noticed that the waiting peaks at charging stations occur after buses stop being dispatched. The fact that this peak of waiting buses happens while the number of charging buses decreases can be explained by the size difference between charging stations in depots and termini. This indicates that a few termini experience long charging queues at the end of the day while the other one already processed theirs.

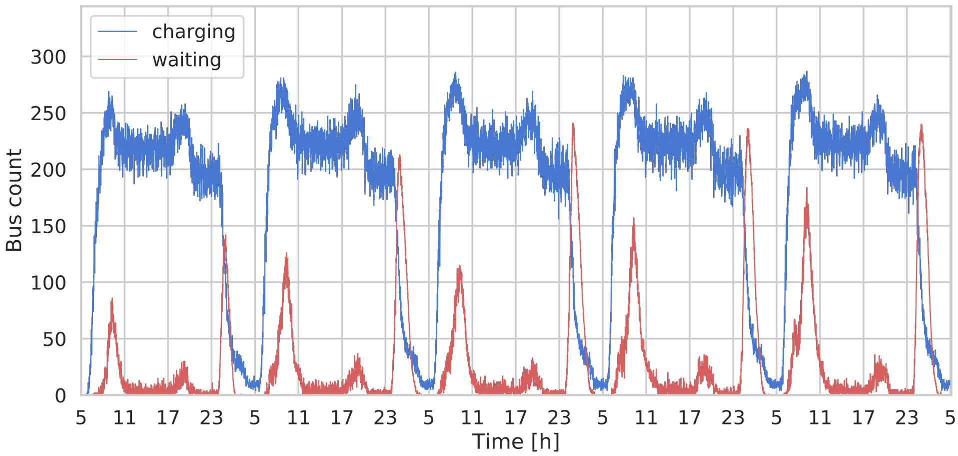


Figure 6.26: Aggregated bus count in charging stations for 450 kW charger power.

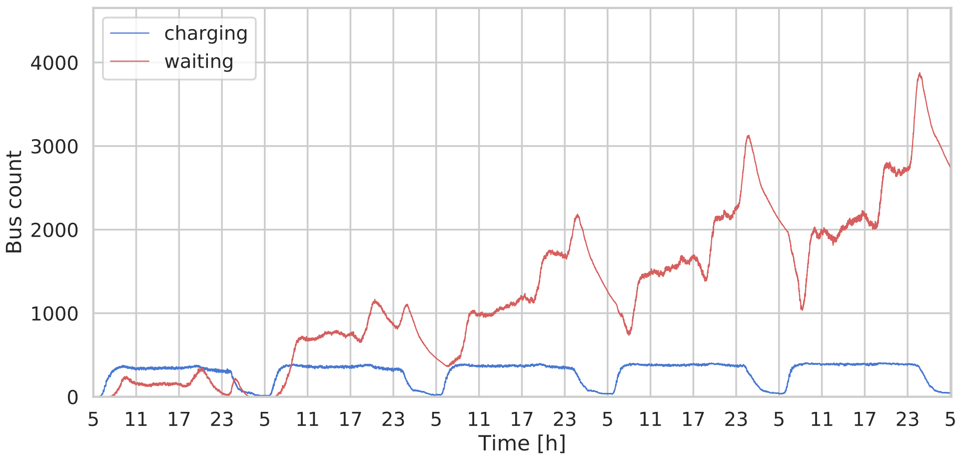


Figure 6.27: Aggregated bus count in charging stations for 300 kW charger power.

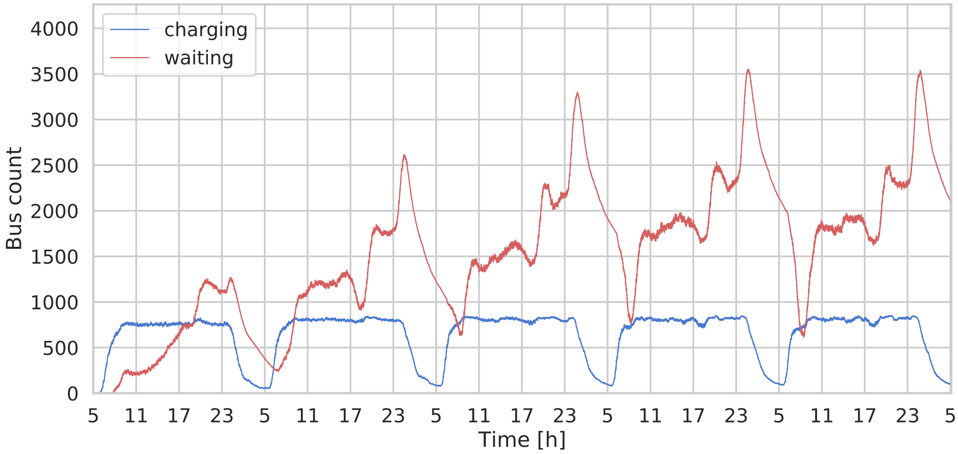


Figure 6.28: Aggregated bus count in charging stations for 150 kW charger power.

6.2.2 Electrification Level

Compared to previous B1 scenario, Figure 6.29 shows that a transition from 100 % to 50 % electrification rate of the bus fleet does not result in a power demand peak divided by two.

Given that the dispatch strategy is set for all scenarios to highest SOC first, electric buses are always favoured over conventional ones. For this reason, more studies are needed where agent types are assigned to bus lines to ensure more meaningful and significant results. Also, more scenarios have to be simulated with different dispatching strategies to compare the actual results.

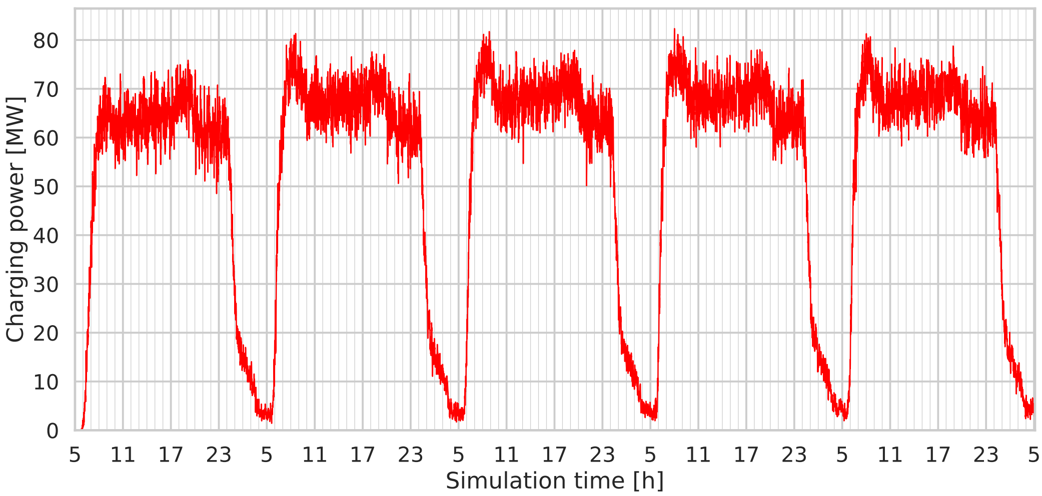


Figure 6.29: Charging power demand for 450 kW and 50 % electrification.

Simulating 25 %, 50 %, 75 %, and 100 % electrification levels was done on 150 kW and 450 kW chargers nominal power cases. Observations from the obtained results are listed in the following subsections.

150 kW **Chargers Nominal Power**

The results in Table A.1 show that higher electrification levels lead to significant increase of off-service energy demand, power demand peak, and missed departures. A transition from 25 % to 100 % electrification level induces a dead-heading energy increase from 9.2 % to 40.6 %).

Such a transition results also in a charging power peak increase from 45 MW to 135 MW, with a higher infrastructure needs from 400 to 1000 chargers.

Missed departures count gets higher, for a higher electrification rate. 25 % electrification leads to only 592 missed dispatches over 5 days, while 100 % electrification results in up to 26,000 missed dispatches.

450 kW **Chargers Nominal Power**

In contrast to the slower charging scenario, setting chargers at 450 kW shows low impact of the electrification level on the dead-heading energy demand (from 6.6 % to 8.1 % energy consumed for off-service trips).

The aggregated charging power peak increases proportionally to the electrification level (from 53 MW to 125 MW). However, this trend is only noticeable for electrification values below 75 %. The power peak does not vary much when going from an electrification level of 75 % to 100 % (around 120 MW) .

Finally, the number of aborted departures shows an increase but not as steep as in the 150 kW scenario (from 400 to 2200 over 5 days of simulation).

6.2.3 Utilisation Threshold

Increasing the utilisation threshold aims at shrinking the infrastructure needs and at tailoring the chargers count to the minimum required to ensure the electric buses fleet operations. For constant parameters, results (see Table A.1) show that a 20 % utilisation threshold cut-off improves the ratio of the aggregated charging power peak over the total installed power capacity (*Peak/Nom*) from 35 % to 95 % and the median power over nominal power ratio from 66 % to 85 %, ensuring a better use of the installed infrastructure.

6.2.4 Queue Prioritisation Strategy

5 different charging prioritising strategies were simulated in this work: random, FIFO, LIFO, HSOC, and LSOC, with 100 % electrification levels and for 150 kW and 450 kW nominal charging power. All the results of these scenarios are summarised in Table A.1.

For the case of 150 kW, with similar electrification levels and usage threshold cut-off, HSOC queuing to charging strategy shows a higher missed dispatches sum comparing to the other strategies, 11,800 versus 2650 for 0 % usage, 7080 versus 2800 for 10 % usage, and 26,660 versus 8500 for 20 % usage.

Analogous, HSOC results show a higher dead-heading energy ratio compared to the other strategies, with 26.8 % versus 20.2 % for 0 % usage, 30.5 % versus 23 % for 10 % usage, and 40.6 % versus 34 % for 20 % usage. On the other hand, LIFO shows a slight advantage compared to the rest in missed journeys count, dead-heading ratio and related off-service energy consumption.

For 450 kW scenarios, different queuing strategies show similar results in all metrics studied. No observations or conclusions can be made in this situation.

6.3 Charging Schedule Optimisation

In order to illustrate the impact of a charging schedule optimisation, a comparison of the data extracted from CityMoS simulation for the biggest bus terminus in Singapore (Boon Lay Interchange) (Figure 6.30) was done with the data resulting from previous results from Gallet et al.![14] work, where the charging schedule is optimised to decrease energy demand fluctuations. This work was done by a fellow intern at TUMCREATE.

The optimisation condition was that, given a number of charging points (17), the charging schedule for the buses has to ensure the best use of the available charging facilities. The charging schedule has also been optimised to avoid big power demand fluctuations within 30 minute long periods. The charging power demand resulting from the optimisation model is presented in Figure 6.31.

From the two curves, the advantage of the optimised charging scheduling is shown, as the second figure show less fluctuations and more stable power demand. This leads to a more grid friendly alternative to the unoptimised simplistic queuing strategies implemented in this work.

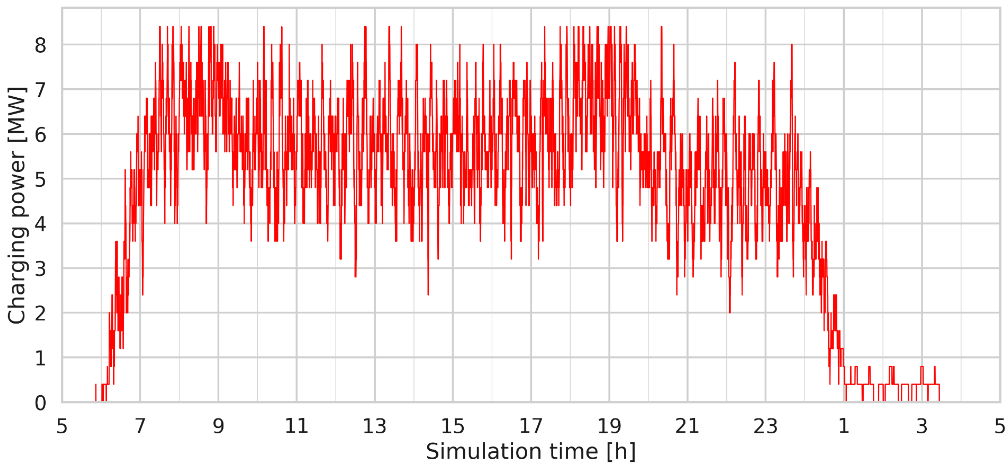


Figure 6.30: Instantaneous charging power demand for Boon Lay Interchange in Singapore without charging schedule optimisation.

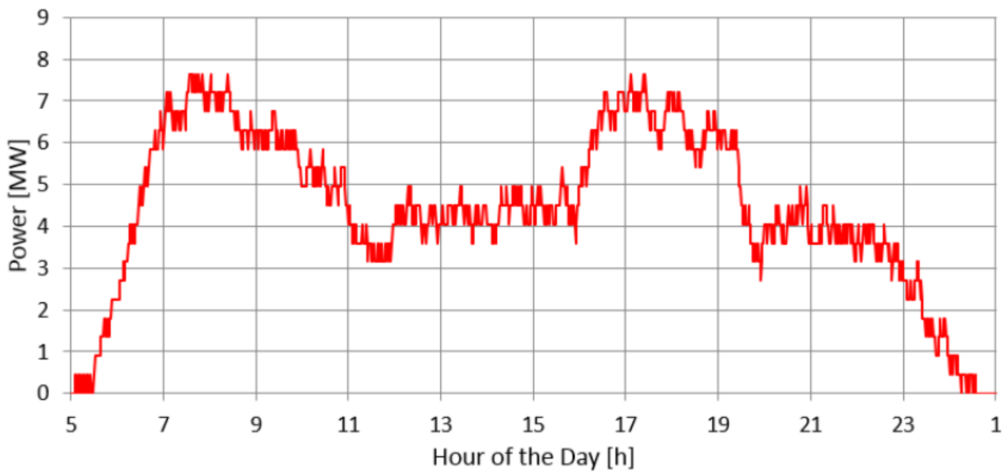


Figure 6.31: Instantaneous charging power demand for Boon Lay Interchange in Singapore with charging schedule optimisation.

6.4 Assumptions and Limitations

The results presented in previous Sections 6.1 and 6.2 were obtained by simulating the electrification of the complete public bus transport system in Singapore described in Section 5.1. To do so, assumptions were made and limitations in the models and implementations are acknowledged here.

- Only battery electric buses were considered in this work. Hybrid or fuel-cell electric buses are out of scope.
- Only a combination of overnight and opportunity end-to-end charging was modelled. Charging at bus stops or on-route charging was not considered.
- Electric buses are always prioritised over conventional buses for dispatch and operations. In case of a partial electrification, conventional buses are dispatched only when no electric buses are available,
- No traffic light or crossroad logic was active during the simulation. Similarly, no dwelling model was used. A fixed 5 seconds dwelling time was set. This simplified implementation is currently needed as a work-around to avoid congestion issues while the driving models are in the process of being improved.
- The battery model is simplified. It does not experience any degradation. The capacity remains constant over days of operation and under harmful conditions.
- All chargers have the same charging power.
- All termini and depots were considered electrified (containing a charging station). The possibility of a combination of electric and conventional structures was not in scope.
- No tailoring on the number of buses used in the simulation was done. 5732 buses were modelled and available for dispatch in all simulated scenarios. This represents more buses than what is strictly required for operation.

- The energy consumption model is simplified. No efficiency map was included for the powertrain (constant efficiency of motor and transmission). HVAC consumption is constant over time.
- The slope of the roads in Singapore was not taken into account at the time of writing this thesis. A new model taking into account slope is currently being implemented.
- The weight of the bus is constant. The passengers' and driver's weights are not yet considered.
- Dead-heading mileage could not be validated or assessed, since no official data for the current LTA bus network in Singapore were released or provided.
- The gathered schedule data is representative of the bus network in 2018. It was cross-referenced with the 2013 bus services from the CEPAS dataset to model a coherent bus network. This model is similar but does not correspond perfectly the reality of the public bus network operations in Singapore in 2013, neither in 2018.
- Only simple strategies were implemented in this work. No values were optimised and more advanced strategies for dispatching and queuing are required.
- No optimisation of the charging schedule was implemented in CityMoS model. The charging operation only results from the dynamics of the bus arrivals and departures in the simulation.
- No waiting time between two charging operations on the same charger.

7 Conclusion and Future Work

7.1 Conclusion

In this Master Thesis, an agent-based simulation was developed to study the impact of partial and full electrification of Singapore public bus network on the service operations and on the charging infrastructure. The goal was to compare different charging strategies and to identify the requirements for a stable transition from fossil-fuelled to battery electric vehicles.

Contributions:
One of the main advantages of the achieved implementation is its flexibility, enabling the exploration of various combinations of electric buses technologies. This work represents the first step towards the identification of the optimal electric bus operation scenario. It builds a stable first version of electric buses simulation with basic strategies and operational decisions. Thus, CityMoS is now able to model a plausible electric bus transportation network, city-wide. Although only 70 scenarios were covered in this thesis, thousands of combinations are still possible to simulate.

Methodology:
To do so, the scientific literature and the market available battery electric buses were reviewed. Stateful buses operations were modelled in CityMoS, calibrated, and validated. After multiple debugging iterations, the simulation presented comparable results to real-world data. Finally, a configuration pipeline starting from input data until processed output was established and documented.

Results:
Even without any optimised strategy, the results obtained from the base scenario show that a full electrification of public buses in Singapore would seem feasible with the installation of 335 ultra-fast chargers, able to deliver up to 450 kW. The resulting charging power demand is limited to 120 MW, representing less than 1 % of the total installed power capacity in Singapore. Varying the nominal power of the chargers showed that implementing a 150 kW infrastructure would not decrease the total aggregated power. In contrast, it decreased the buses availability and increased the number of required chargers. Tuning the electrification threshold showed that high ratios of electric buses in the bus fleet can only be competitive when charging stations are equipped with chargers delivering more than 450 kW. The results from varying the charging strategy and from comparing CityMoS output to a simulation with optimised charging schedule emphasise the need to work further on more advanced strategies.

It may be concluded that the complexity of a city-scale simulation is greater than modelling one or few bus lines and routes. As many routes share the same charging infrastructure, a bus network must be studied as whole system. Although a model is never perfectly representative of the real-world, it can always be further enhanced to represent the actual behaviour of the system with more accuracy and to help real-world planning by simulating future scenarios.

7.2 Outlook

Implementation of more advanced features and strategies is now possible and required:

- Updating Singapore infrastructure, bus routes, and services to the latest stand can be advantageous. The 2018 bus network should represent the base ground for electrification scenarios.
- The powertrain model needs to include a dynamic efficiency map and to calculate the energy consumption according to road conditions such as the slope.
- A realistic road congestion in the roads needs to be modelled with more dense traffic in peak hours. The previously implemented dynamic dwelling model based on passenger demand needs to be debugged and must replace the current fixed time dwelling model. These two parameters are likely to lead to an increase of the energy consumption of the buses during service. This would improve the implemented energy consumption model, considered too optimistic in the current validation phase.
- New dispatching and charging strategies need to be designed and implemented. Queuing theory algorithms can be explored. Electricity pricing and grid stability can be considered to optimise the charging schedule.
- Grid demand side response and intelligent energy infrastructure, combined to renewable energy generation represent a wide potential field of research. Assuming 5500 battery electric buses available in the city, we would have at disposal more than 800 MWh of mobile energy storage capacity. Well managed, this resource could help stabilising the electric grid, even under highly fluctuating renewable energy intakes.

A Annexes

A.1 Available Electric Buses Technologies

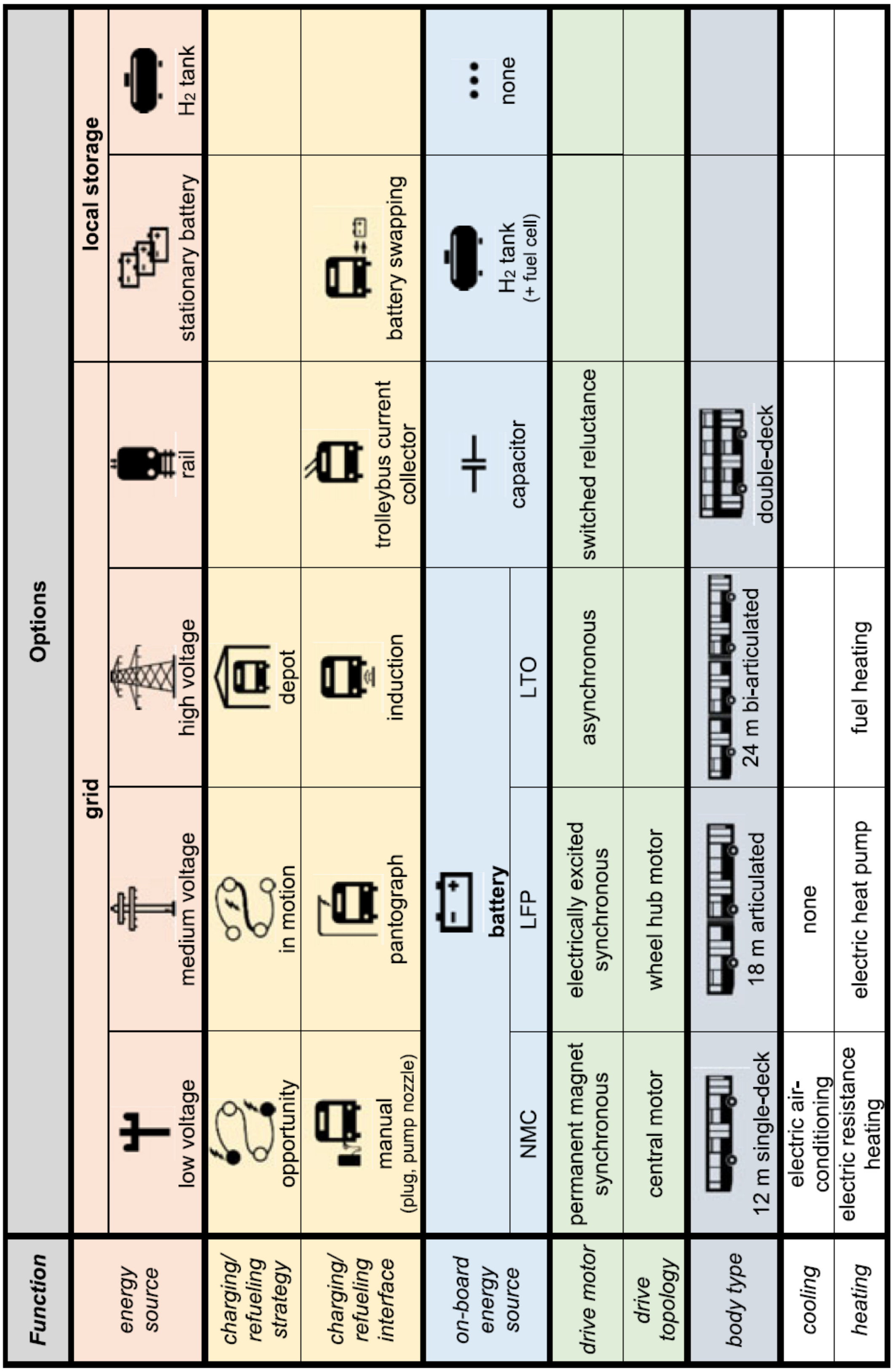


Figure A.1: Morphological matrix of available electric buses technologies (image imported from [34]).

A.2 Deadlock Issues in Singapore Map

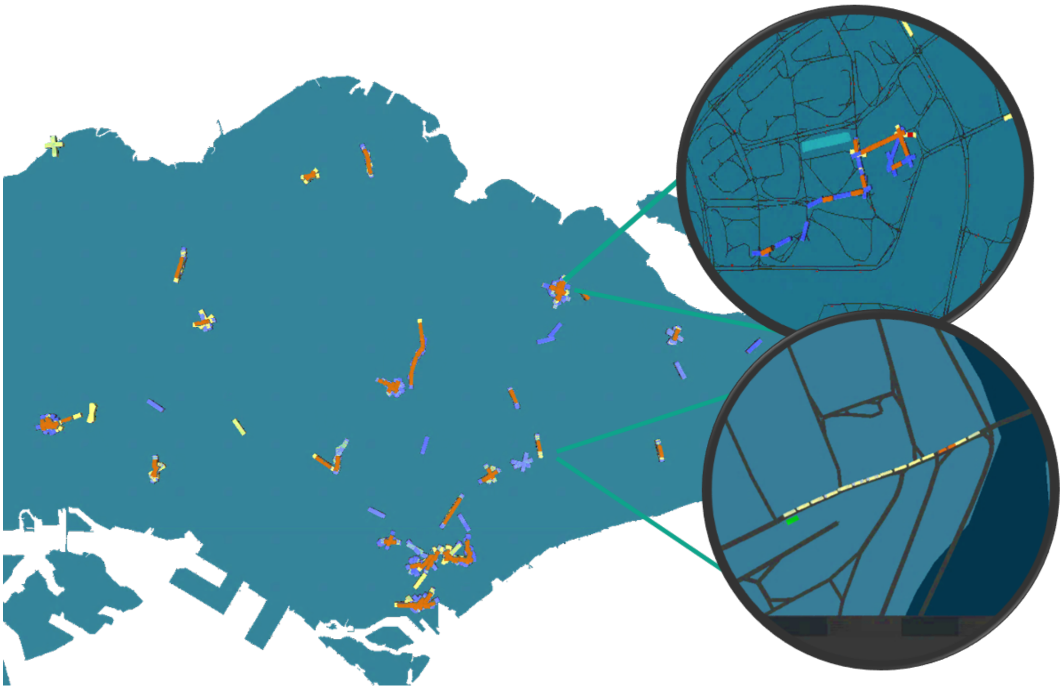


Figure A.2: Deadlocks in Singapore map.

A.3 Example of Bus Route Issues

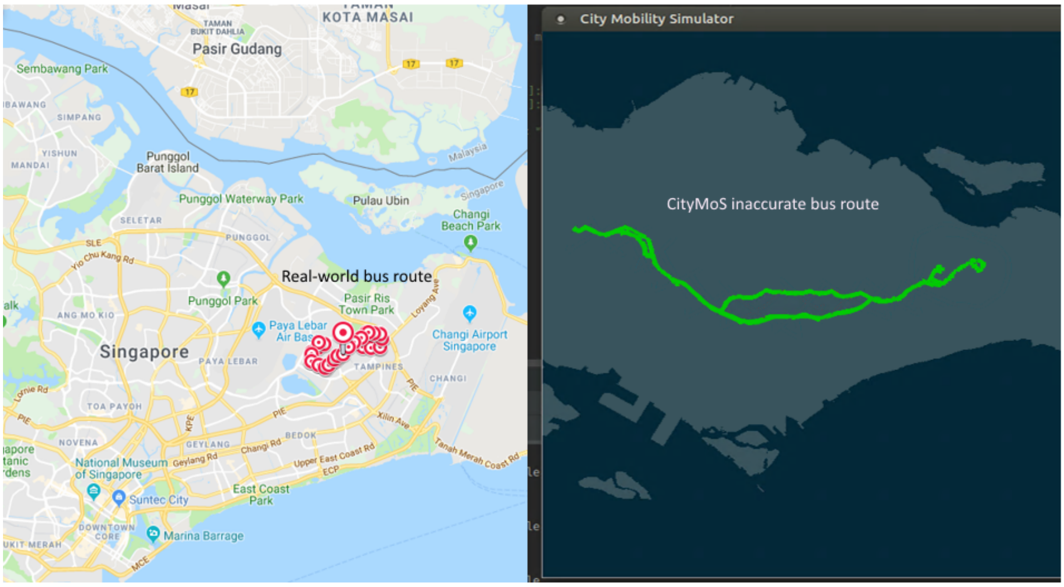


Figure A.3: Issues in bus routes in Singapore.

A.4 Chargers Count Calibration Analysis (B0 Scenario)

The following figure shows the distribution of bus chargers in Singapore for the scenario B0 before removing the superfluous chargers. All parking spots at termini are equipped with one charger. All depots are initialised with 100 chargers.

The total number of chargers defined is shown in blue. The identified chargers count with at least 20 % usage threshold (UT) per terminus and depot is shown in green.

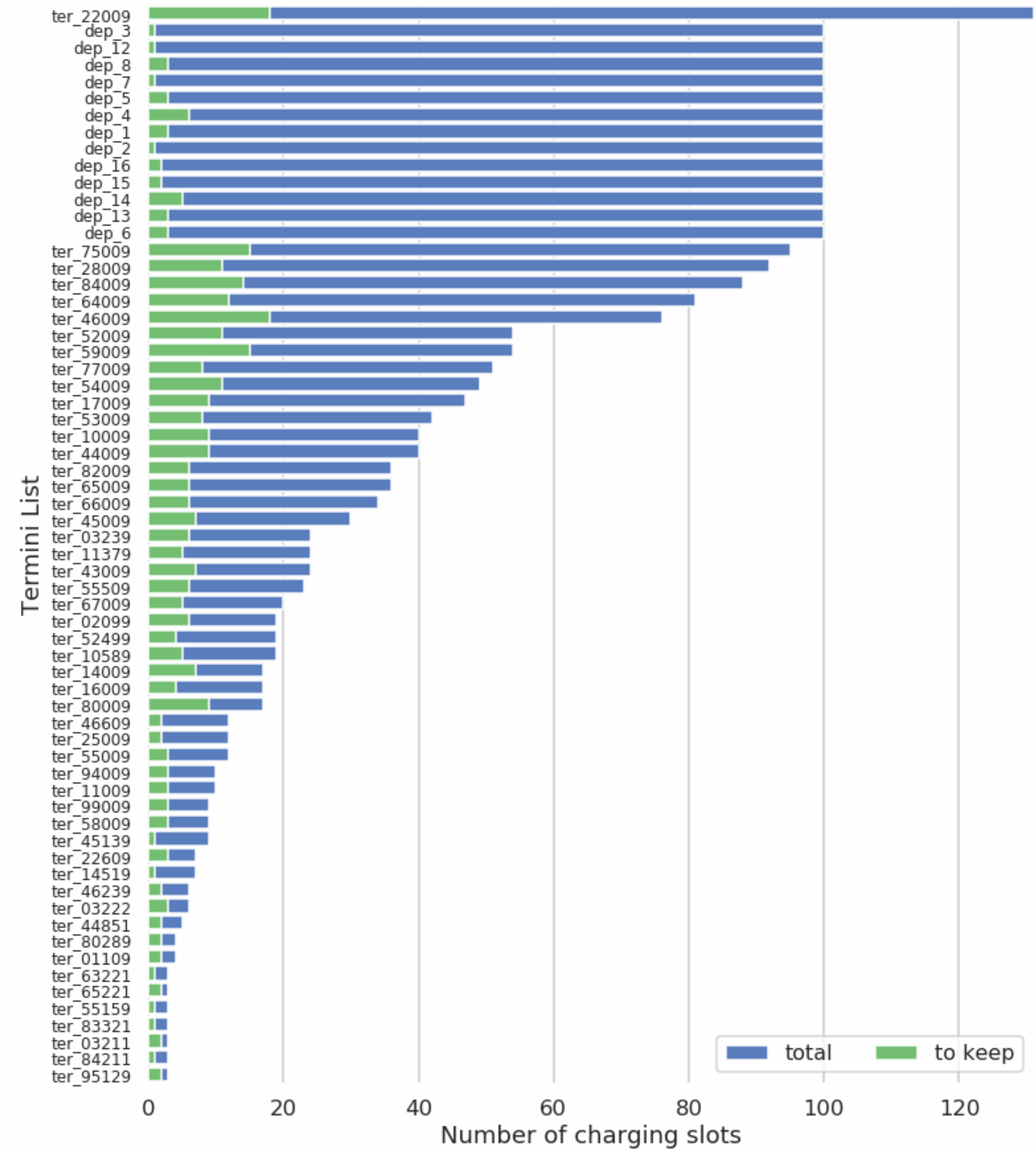


Figure A.4: Base Scenario (B0) chargers count calibration analysis at 20 % usage threshold with 450 kW charging power.

A.5 Chargers Count Calibration Results (B0 Scenario)

The following figure shows the distribution of the charger in Singapore for the scenario B0 after removing the superfluous chargers.

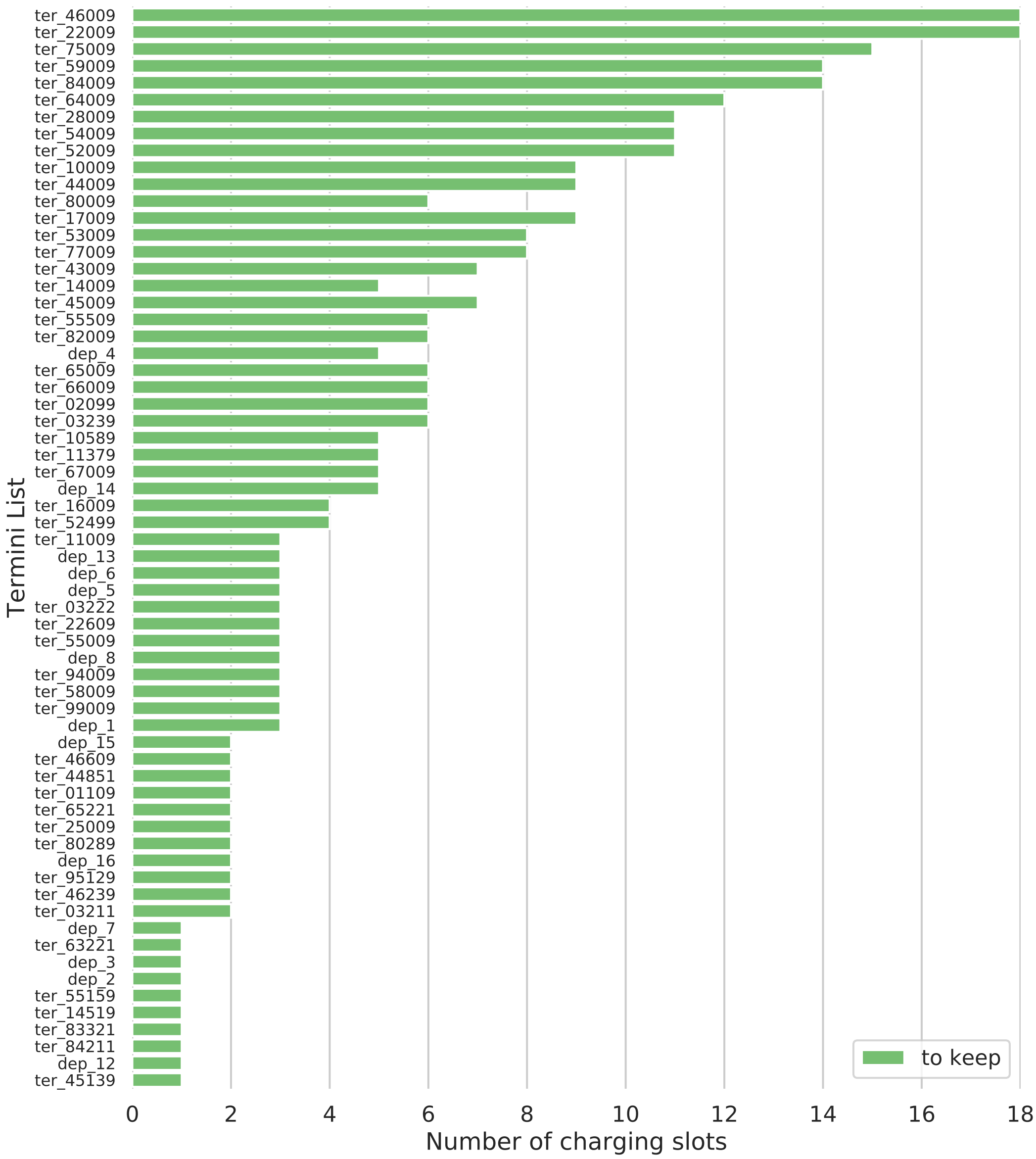


Figure A.5: Base Scenario (B0) chargers count calibration results at 20 % usage threshold with 450 kW charging power.

A.6 Scenarios Simulation Results Overview

Table A.1: Results of all 70 simulated scenarios.

Simulation Config	Buses	Deadhead in %	Distance in km	Missed Sum	Chargers	Power Nom. in kW	Power Peak in kW	Peak/Nom	Consumption in MWh	Deadhead E. in MWh
150-100-0-RANDOM	5732	30.72	256.7	2583	2742	411.3	145.5	35%	1441.1	362.3
150-100-10-FIFO	5732	34.9	272.5	2825	1022	153.3	128.4	84%	1439.9	434.9
150-25-0-HSOC	5232	16.59	239.3	576	2742	411.3	45.8	11%	605.2	62.1
150-50-0-HSOC	5331	25.17	259.8	1244	2742	411.3	87.4	21%	1118.3	199.4
150-75-0-HSOC	5400	30.43	272.4	2281	2742	411.3	127.4	31%	1405.6	344
150-100-0-FIFO	5732	30.76	256.5	2692	2742	411.3	146.1	36%	1432.8	362.2
150-100-0-LIFO	5732	31.12	257.7	2780	2742	411.3	141	34%	1432.9	366.9
150-100-0-LSOC	5732	30.62	256	2675	2742	411.3	141.6	34%	1436.5	360.6
150-100-20-FIFO	5732	48.62	330.8	8360	930	139.5	134.5	96%	1403.3	723.1
150-25-10-HSOC	5267	16.57	237.6	592	460	69	44.9	65%	595.4	60.5
150-50-10-HSOC	5307	24.9	260.5	1086	779	116.85	83.3	71%	1100.7	190
150-75-10-HSOC	5399	30.3	272.4	2097	1001	150.15	116.2	77%	1389.5	339.2
150-100-10-HSOC	5732	44.31	309.2	7081	963	144.45	133	92%	1414.2	620.6
150-25-20-HSOC	5264	17.01	239	593	399	59.85	43.1	72%	597.1	62.2
150-50-20-HSOC	5356	24.6	256.8	1186	706	105.9	80.7	76%	1080.2	183.7
150-75-20-HSOC	5524	31.48	270.5	2261	912	136.8	113.3	83%	1384.1	353.5
150-100-20-HSOC	5732	56.61	345.6	26668	872	130.8	126.6	97%	1257.8	860.4
150-100-10-LIFO	5732	31.94	261.2	2638	1023	153.45	129.8	85%	1444.5	383.5
150-100-20-LIFO	5732	44.7	313.2	6018	933	139.95	133.4	95%	1428.1	635.3
150-100-10-LSOC	5732	35.26	274	2823	1025	153.75	132.2	86%	1443.3	441.2
150-100-20-LSOC	5732	50.68	342.8	8977	932	139.8	136.4	98%	1388.1	775.6
150-100-10-RANDOM	5732	31.7	259.7	2838	1030	154.5	127.8	83%	1433.7	376.3
150-100-20-RANDOM	5732	47.33	324.7	7567	933	139.95	136	97%	1407.1	691.3
150-100-0-HSOC	5732	39.82	295.1	11791	2742	411.3	152.6	37%	1425.6	522.8
200-100-15-HSOC	5732	32.35	258.5	8913	706	141.2	128.6	91%	1402.6	376.4
300-100-0-HSOC	5654	20.16	229.8	1817	2742	822.6	132.1	16%	1445.4	208.4
300-50-10-HSOC	5279	14.88	231.6	880	385	115.5	83.4	72%	1123.9	111.7
300-100-10-HSOC	5542	17.79	224.5	2192	478	143.4	110.3	77%	1441.9	179.6
300-50-0-HSOC	5268	17.3	238.8	1360	2742	822.6	87.3	11%	1131.1	130.5

Table A.1: Results of all 70 simulated scenarios.

Simulation Config	**Buses**	**Deadhead in** %	**Distance in** km	**Missed Sum**	**Chargers**	**Power Nom. in** kW	**Power Peak in** kW	**Peak/Nom**	**Consumption in** MWh	**Deadhead E. in** MWh
300-50-20-HSOC	5252	15.9	235.7	831	345	103.5	79.8	77%	1122.6	119.2
300-100-20-HSOC	5732	39.64	275.2	14203	420	126	119.1	95%	1371.3	482.9
400-100-15-HSOC	5613	18	225	2196	387	154.8	123.6	80%	1456.5	182.2
450-50-0-HSOC	5207	13.79	232.3	941	2742	1233.9	90.9	7%	1140.5	103.6
450-100-0-HSOC	5346	12.92	219.8	2150	2742	1233.9	119.3	10%	1441	122.8
450-100-0-FIFO	5372	13.49	220.8	1902	2742	1233.9	125.1	10%	1444.8	129.8
450-100-0-LIFO	5387	13.39	219.5	2066	2742	1233.9	124.9	10%	1451.2	128.9
450-100-0-LSOC	5397	13.26	218.8	2053	2742	1233.9	119.7	10%	1454.6	127.3
450-100-0-RANDOM	5331	13.28	222	1850	2742	1233.9	121.1	10%	1447.7	127.3
450-25-0-HSOC	5098	10.87	229.9	524	2742	1233.9	55.7	5%	679.3	50.1
450-75-0-HSOC	4812	14.03	249.8	1505	2742	1233.9	120.4	10%	1418.2	134.6
450-100-10-FIFO	5305	13.22	222.1	2205	388	174.6	116.1	66%	1443.6	126.7
450-100-20-FIFO	5391	13.3	218.7	2275	336	151.2	115.6	76%	1433.8	126.7
450-25-10-HSOC	5111	10.7	232.7	481	235	105.75	51.5	49%	676.9	47.5
450-50-10-HSOC	5189	12.05	228.2	788	296	133.2	87.9	66%	1148.6	94.2
450-75-10-HSOC	4781	13.27	248.5	1656	393	176.85	116	66%	1420.5	126.8
450-100-10-HSOC	5339	13.15	220.7	2148	381	171.45	117.3	68%	1445.1	125.7
450-25-20-HSOC	5106	10.93	229.7	510	195	87.75	53.9	61%	681.6	50.8
450-50-20-HSOC	5256	12.56	226.7	775	262	117.9	82.3	70%	1124.3	94.6
450-75-20-HSOC	4861	13.37	245.1	1532	344	154.8	111.2	72%	1411.4	127.5
450-100-20-HSOC	5394	13.35	218.9	2179	333	149.85	112.9	75%	1446.4	127.9
450-100-10-LIFO	5402	12.87	218.3	1737	387	174.15	115.2	66%	1447.5	122.5
450-100-20-LIFO	5409	13.11	217.7	2172	340	153	111.9	73%	1437.9	124.5
450-100-10-LSOC	5393	12.96	218.5	1939	387	174.15	116.9	67%	1451.1	123.9
450-100-20-LSOC	5366	13.06	220.2	1775	338	152.1	114.4	75%	1451.7	125.4
450-100-10-RANDOM	5357	12.92	220	1898	386	173.7	118.1	68%	1454	124.1
450-100-20-RANDOM	5384	13.1	218.9	2053	339	152.55	114.6	75%	1439	124.7
600-100-0-HSOC	5347	12.1	217.9	2073	2742	1645.2	123.9	8%	1432.5	113.7
600-50-0-HSOC	5184	11.18	226.2	778	2742	1645.2	98.6	6%	1144.8	86.4

Table A.1: Results of all 70 simulated scenarios.

Simulation Config	**Buses**	**Deadhead in** %	**Distance in** km	**Missed Sum**	**Chargers**	**Power Nom. in** kW	**Power Peak in** kW	**Peak/Nom**	**Consumption in** MWh	**Deadhead E. in** MWh
600-50-10-HSOC	5197	11.18	225.7	767	268	160.8	90.8	56%	1137.4	85
600-100-10-HSOC	5325	12.14	219.3	1880	318	190.8	118.6	62%	1448.6	114.3
600-50-20-HSOC	5192	11.22	226.2	683	237	142.2	88.3	62%	1142.6	85
600-100-20-HSOC	5314	12.15	219.9	1811	269	161.4	115.4	71%	1456.6	115.4

A.7 Instantaneous Charging Power Demand

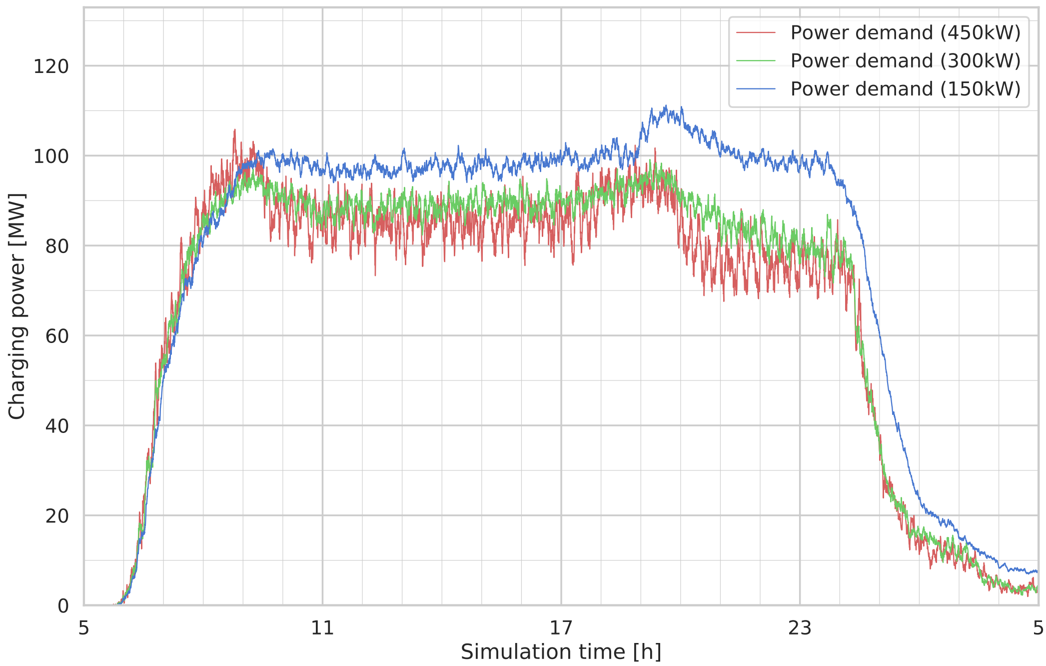


Figure A.6: Instantaneous aggregated charging power demand for 450, 300, and 150 kW during the first operation day with calibrated chargers count (333 chargers for 450 kW, 420 for 300 kW and 872 for 150 kW).

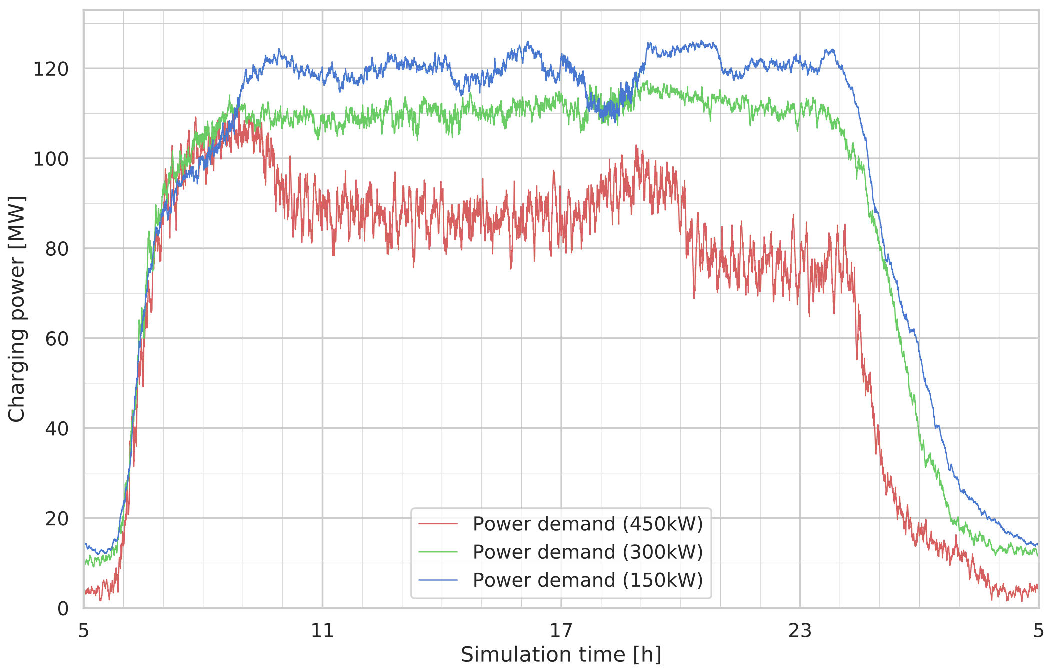


Figure A.7: Instantaneous aggregated charging power demand for 450, 300, and 150 kW during the fifth operation day with calibrated chargers count (333 chargers for 450 kW, 420 for 300 kW and 872 for 150 kW).

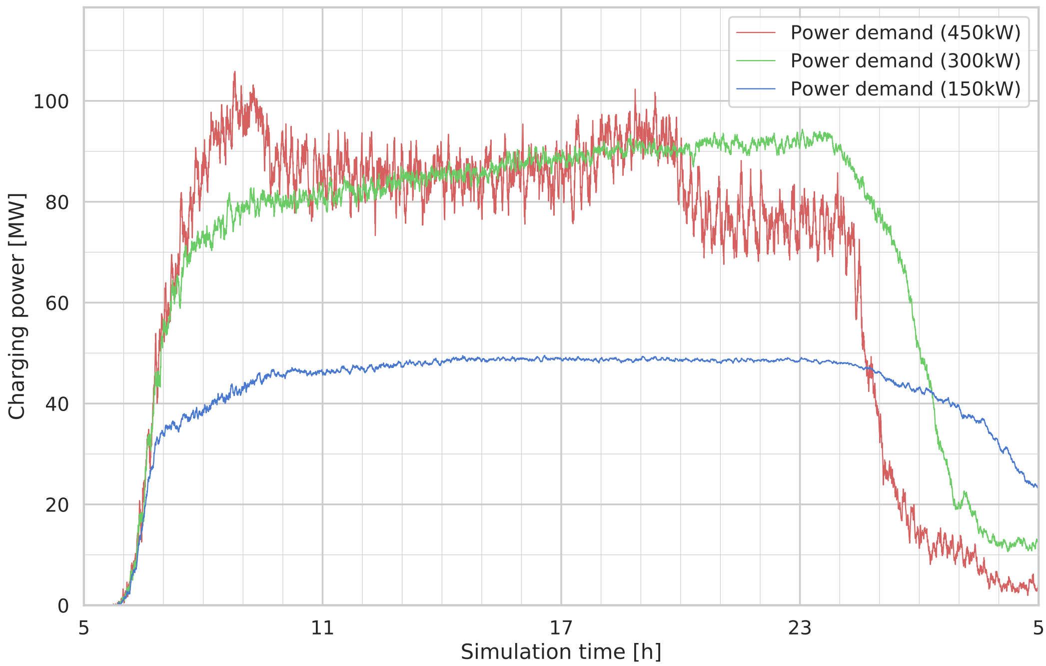


Figure A.8: Instantaneous aggregated charging power demand for 450, 300, and 150 kW during day 1 operations with same chargers count (333 chargers for all cases).

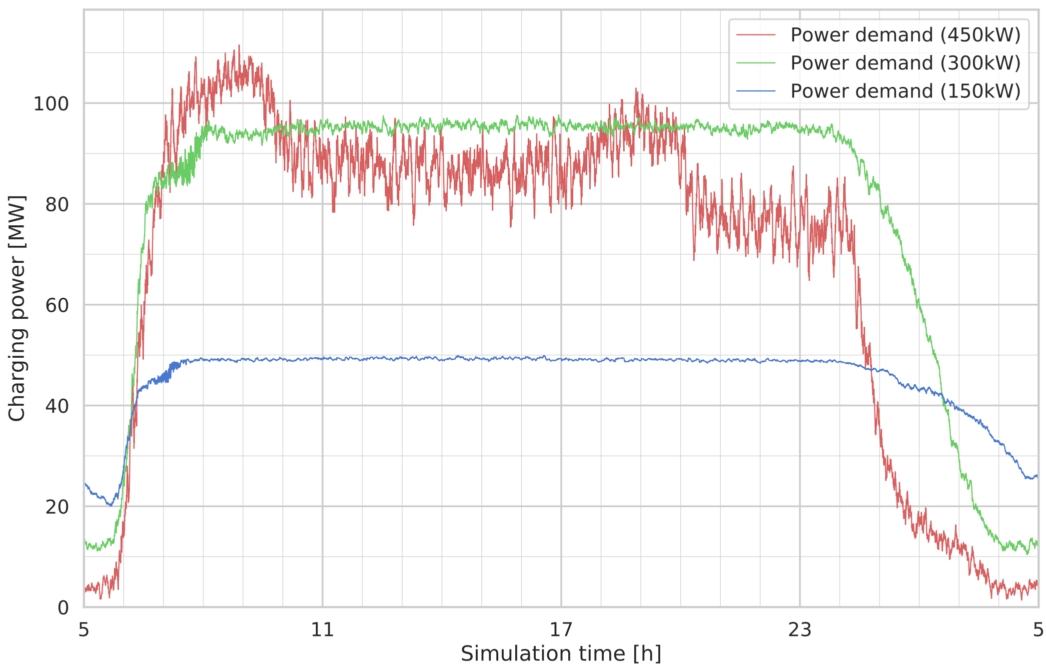


Figure A.9: Instantaneous aggregated charging power demand for 450, 300, and 150 kW during day 5 operations with same chargers count (333 chargers for all cases).

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Bibliography

[1] Korhola, E.-R. and Yliopisto, H. 'The Rise and Fall of the Kyoto Protocol: Climate Change as a Political Process'. OCLC: 924705427. Helsinki: University of Helsinki, 2014.

[2] United Nations (UN). *COP21, Adoption of the Paris Agreement*. 2015.

[3] Hosking, J.; Dora, C., and Mudu, P. *Health in the Green Economy: Health Co-Benefits of Climate Change Mitigation: Transport Sector*. Geneva, Switzerland: World Health Organization, 2011. 144 pp. ISBN: 978-92-4-150291-7.

[4] Song, Q.; Wang, Z.; Wu, Y.; Li, J.; Yu, D.; Duan, H., and Yuan, W. 'Could Urban Electric Public Bus Really Reduce the GHG Emissions: A Case Study in Macau?' In: *Journal of Cleaner Production* 172 (Nov. 2017), pp. 2133–2142. ISSN: 09596526. DOI: 10.1016/j.jclepro.2017.11.206.

[5] Miles, J. and Potter, S. 'Developing a Viable Electric Bus Service: The Milton Keynes Demonstration Project'. In: *Research in Transportation Economics* 48 (Dec. 2014), pp. 357–363. ISSN: 07398859. DOI: 10.1016/j.retrec.2014.09.063.

[6] Pihlatie, M.; Kukkonen, S.; Halmeaho, T.; Karvonen, V., and Nylund, N.-O. 'Fully Electric City Buses - The Viable Option'. In: *2014 IEEE International Electric Vehicle Conference (IEVC)*. 2014 IEEE International Electric Vehicle Conference (IEVC). Florence, Italy: IEEE, Dec. 2014, pp. 1–8. ISBN: 978-1-4799-6075-0. DOI: 10.1109/IEVC.2014.7056145.

[7] United Nations and Department of Economic and Social Affairs. *World Urbanization Prospects, the 2014 Revision: Highlights*. 2014. ISBN: 978-92-1-056809-8.

[8] Mahmoud, M.; Garnett, R.; Ferguson, M., and Kanaroglou, P. 'Electric Buses: A Review of Alternative Powertrains'. In: *Renewable and Sustainable Energy Reviews* 62 (Sept. 2016), pp. 673–684. ISSN: 13640321. DOI: 10.1016/j.rser.2016.05.019.

[9] Lajunen, A. and Lipman, T. 'Lifecycle Cost Assessment and Carbon Dioxide Emissions of Diesel, Natural Gas, Hybrid Electric, Fuel Cell Hybrid and Electric Transit Buses'. In: *Energy* 106 (July 2016), pp. 329–342. ISSN: 03605442. DOI: 10.1016/j.energy.2016.03.075.

[10] Teoh, L. E.; Khoo, H. L.; Goh, S. Y., and Chong, L. M. 'Scenario-Based Electric Bus Operation: A Case Study of Putrajaya, Malaysia'. In: *International Journal of Transportation Science and Technology* (Sept. 2017). ISSN: 20460430. DOI: 10.1016/j.ijtst.2017.09.002.

[11] Gao, Z.; Lin, Z.; LaClair, T. J.; Liu, C.; Li, J.-M.; Birky, A. K., and Ward, J. 'Battery Capacity and Recharging Needs for Electric Buses in City Transit Service'. In: *Energy* 122 (Mar. 2017), pp. 588–600. ISSN: 03605442. DOI: 10.1016/j.energy.2017.01.101.

[12] Xylia, M.; Leduc, S.; Patrizio, P.; Kraxner, F., and Silveira, S. 'Locating Charging Infrastructure for Electric Buses in Stockholm'. In: *Transportation Research Part C: Emerging Technologies* 78 (May 2017), pp. 183–200. ISSN: 0968090X. DOI: 10.1016/j.trc.2017.03.005.

[13] De Filippo, G.; Marano, V., and Sioshansi, R. 'Simulation of an Electric Transportation System at The Ohio State University'. In: *Applied Energy* 113 (Jan. 2014), pp. 1686–1691. ISSN: 03062619. DOI: 10.1016/j.apenergy.2013.09.011.

[14] Gallet, M.; Massier, T., and Hamacher, T. 'Estimation of the Energy Demand of Electric Buses Based on Real-World Data for Large-Scale Public Transport Networks'. In: *Applied Energy* 230 (Nov. 2018), pp. 344–356. ISSN: 03062619. DOI: 10.1016/j.apenergy.2018.08.086.

[15] Benz, M.; Gürges, K., and Borufka, S. *Techview Report Electric Buses*. Frauenhofer-zentrum for International Management and Economy, European Business and Technology Center EBTC. 2015.

[16] Laurikko, J.; Pihlatie, M.; Nylund, N.-O.; Halmeaho, T.; Kukkonen, S.; LEHTINEN, A.; KARVONEN, V.; MÄKINEN, R., and AHTIAINEN, S. 'Electric City Bus and Infrastructure Demonstration Environment in Espoo, Finland'. In: *Proc. International Electric Vehicle Symposium and Exhibition (EVS28)*. International Electric Vehicle Symposium and Exhibition (EVS28). KINTEX, Goyang, Korea, May 2015, pp. 1–11.

[17] ZeEUS Project. *ZeEUS eBus Report: An Overview of Electric Buses in Europe*. Zero Emission Urban Bus System (ZeEUS). 2018.

[18] Xylia, M. and Silveira, S. 'On the Road to Fossil-Free Public Transport: The Case of Swedish Bus Fleets'. In: *Energy Policy* 100 (Jan. 2017), pp. 397–412. ISSN: 03014215. DOI: 10.1016/j.enpol.2016.02.024.

[19] Li, J.-Q. 'Battery-Electric Transit Bus Developments and Operations: A Review'. In: *International Journal of Sustainable Transportation* 10.3 (Mar. 15, 2016), pp. 157–169. ISSN: 1556-8318, 1556-8334. DOI: 10.1080/15568318.2013.872737.

[20] Marcon. *Electric Bus Feasibility Study - Edmonton Canada*. June 2016.

[21] Wang, Y.; Huang, Y.; Xu, J., and Barclay, N. 'Optimal Recharging Scheduling for Urban Electric Buses: A Case Study in Davis'. In: *Transportation Research Part E: Logistics and Transportation Review* 100 (Apr. 2017), pp. 115–132. ISSN: 1366-5545. DOI: 10.1016/j.tre.2017.01.001.

[22] Grütter, J. M. *Real World Performance of Hybrid and Electric Buses - Case Study Shengzhou, Shenzhen and Bogota*. Gruetter Consulting, Dec. 2014.

[23] Land Transport Guru. *Electric Buses to Be Procured by LTA*. Dec. 14, 2017. URL: http://landtransportguru.net/electric-buses-to-be-procured-by-lta/ (visited on 06/25/2018).

[24] Chediak, M. *Electric Buses Will Take Over Half the World Fleet by 2025*. Jan. 2, 2018. URL: https://www.bloomberg.com/news/articles/2018-02-01/electric-buses-will-take-over-half-the-world-by-2025 (visited on 11/21/2018).

[25] Kailasam, C.; Huang, J.; Kar, S., and Leveque, F. *Strategic Analysis of Global Hybrid and Electric Heavy-Duty Transit Bus Market*. NC7C-18. Frost and Sullivan, Sept. 2013.

[26] Mohamed, M.; Ferguson, M., and Kanaroglou, P. 'What Hinders Adoption of the Electric Bus in Canadian Transit? Perspectives of Transit Providers'. In: *Transportation Research Part D: Transport and Environment* (Sept. 2017). ISSN: 13619209. DOI: 10.1016/j.trd.2017.09.019.

[27] Rogge, M.; v. d. Hurk, E.; Larsen, A., and Sauer, D. U. 'Electric Bus Fleet Size and Mix Problem with Optimization of Charging Infrastructure'. In: *Applied Energy* 211 (Feb. 2018). RWTH Aachen, pp. 282–295. ISSN: 03062619. DOI: 10.1016/j.apenergy.2017.11.051.

[28] Xu, Y.; Gbologah, F. E.; Lee, D.-Y.; Liu, H.; Rodgers, M. O., and Guensler, R. L. 'Assessment of Alternative Fuel and Powertrain Transit Bus Options Using Real-World Operations Data: Life-Cycle Fuel and Emissions Modeling'. In: *Applied Energy* 154 (Sept. 2015), pp. 143–159. ISSN: 03062619. DOI: 10.1016/j.apenergy.2015.04.112.

[29] Olsson, O.; Grauers, A., and Pettersson, S. 'Method to Analyze Cost Effectiveness of Different Electric Bus Systems'. In: *29th International Electric Vehicle Symposium 2016 (EVS29)*. 29th International Electric Vehicle Symposium 2016 (EVS29). 2017-10-31. Montréal, Canada, 2016, pp. 604–615. ISBN: 978-1-5108-3270-1.

[30] Ke, B.-R.; Chung, C.-Y., and Chen, Y.-C. 'Minimizing the Costs of Constructing an All Plug-in Electric Bus Transportation System: A Case Study in Penghu'. In: *Applied Energy* 177 (Sept. 2016), pp. 649–660. ISSN: 03062619. DOI: 10.1016/j.apenergy.2016.05.152.

[31] Williamson, S. S.; Wirasingha, S. G., and Emadi, A. 'Comparative Investigation of Series and Parallel Hybrid Electric Drive Trains for Heavy-Duty Transit Bus Applications'. In: *2006 IEEE Vehicle Power and Propulsion Conference*. 2006 IEEE Vehicle Power and Propulsion Conference. Windsor, UK: IEEE, Sept. 2006, pp. 1–10. ISBN: 978-1-4244-0158-1 978-1-4244-0159-8. DOI: 10.1109/VPPC.2006.364354.

[32] Bossel, U. 'Does a Hydrogen Economy Make Sense?' In: *Proceedings of the IEEE* 94.10 (Oct. 2006), pp. 1826–1837. ISSN: 0018-9219, 1558-2256. DOI: 10.1109/JPROC.2006.883715.

[33] Mulligan, L. *Developing Sustainable Public Transport: The Electric Bus Charging Project*. Apr. 24, 2017. URL: http://www.engineersjournal.ie/2017/04/24/ebus-electric-bus-transport/ (visited on 11/13/2018).

[34] Göhlich, D.; Fay, T.-A.; Jefferies, D.; Lauth, E.; Kunith, A., and Zhang, X. 'Design of Urban Electric Bus Systems'. In: *Design Science* 4 (2018). ISSN: 2053-4701. DOI: 10.1017/dsj.2018.10.

[35] Mohamed, M.; Farag, H.; El-Taweel, N., and Ferguson, M. 'Simulation of Electric Buses on a Full Transit Network: Operational Feasibility and Grid Impact Analysis'. In: *Electric Power Systems Research* 142 (Jan. 2017), pp. 163–175. ISSN: 03787796. DOI: 10.1016/j.epsr.2016.09.032.

[36] European Automobile Manufacturers Association. *Charging of Electric Buses - ACEA Recommendations*. May 2017. URL: https://www.oppcharge.org/.

[37] Trippe, A. E.; Arunachala, R.; Massier, T.; Jossen, A., and Hamacher, T. 'Charging Optimization of Battery Electric Vehicles Including Cycle Battery Aging'. In: *IEEE PES Innovative Smart Grid Technologies, Europe*. 2014 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe). Istanbul, Turkey: IEEE, Oct. 2014, pp. 1–6. ISBN: 978-1-4799-7720-8. DOI: 10.1109/ISGTEurope.2014.7028735.

[38] Kunith, A.; Mendelevitch, R., and Goehlich, D. 'Electrification of a City Bus Network—An Optimization Model for Cost-Effective Placing of Charging Infrastructure and Battery Sizing of Fast-Charging Electric Bus Systems'. In: *International Journal of Sustainable Transportation* 11.10 (Nov. 26, 2017), pp. 707–720. ISSN: 1556-8318, 1556-8334. DOI: 10.1080/15568318.2017.1310962.

[39] Kontou, A. and Miles, J. 'Electric Buses: Lessons to Be Learnt from the Milton Keynes Demonstration Project'. In: *Procedia Engineering* 118 (2015), pp. 1137–1144. ISSN: 18777058. DOI: 10.1016/j.proeng.2015.08.455.

[40] Vepsäläinen, J.; Kivekäs, K.; Otto, K.; Lajunen, A., and Tammi, K. 'Development and Validation of Energy Demand Uncertainty Model for Electric City Buses'. In: *Transportation Research Part D: Transport and Environment* 63 (Aug. 2018), pp. 347–361. ISSN: 13619209. DOI: 10.1016/j.trd.2018.06.004.

[41] Genikomsakis, K. N. and Mitrentsis, G. 'A Computationally Efficient Simulation Model for Estimating Energy Consumption of Electric Vehicles in the Context of Route Planning Applications'. In: *Transportation Research Part D: Transport and Environment* 50 (Jan. 2017), pp. 98–118. ISSN: 13619209. DOI: 10.1016/j.trd.2016.10.014.

[42] Perrotta, D.; Macedo, J. L.; Rossetti, R. J.; Sousa, J. F. d.; Kokkinogenis, Z.; Ribeiro, B., and Afonso, J. L. 'Route Planning for Electric Buses: A Case Study in Oporto'. In: *Procedia - Social and Behavioral Sciences* 111 (Feb. 2014), pp. 1004–1014. ISSN: 18770428. DOI: 10.1016/j.sbspro.2014.01.135.

[43] Qin, N.; Gusrialdi, A.; Paul Brooker, R., and T-Raissi, A. 'Numerical Analysis of Electric Bus Fast Charging Strategies for Demand Charge Reduction'. In: *Transportation Research Part A: Policy and Practice* 94 (Dec. 2016), pp. 386–396. ISSN: 09658564. DOI: 10.1016/j.tra.2016.09.014.

[44] Wen, M.; Linde, E.; Ropke, S.; Mirchandani, P., and Larsen, A. 'An Adaptive Large Neighborhood Search Heuristic for the Electric Vehicle Scheduling Problem'. In: *Computers & Operations Research* 76 (Dec. 2016), pp. 73–83. ISSN: 03050548. DOI: 10.1016/j.cor.2016.06.013.

[45] Noosa Council & TransLink Division. *Prefeasibility Study of Electric Bus Routes in Noosa - Planning Report*. Dec. 2014.

[46] Gallo, J.-B.; Bloch-Rubin, T., and Tomić, J. *Peak Demand Charges and Electric Transit Buses*. Jan. 10, 2014.

[47] O'Donovan, A.; Frith, J., and McKerracher, C. *Electric Buses in Cities - Driving Towards Cleaner Air and Lower CO2*. Mar. 29, 2018.

[48] Massier, T.; Recalde, D.; Sellmair, R.; Gallet, M., and Hamacher, T. 'Electrification of Road Transport in Singapore and Its Integration into the Power System'. In: *Energy Technology* 6.1 (Jan. 2018), pp. 21–32. ISSN: 21944288. DOI: 10.1002/ente.201700652.

[49] Ting, W. P. *Billion-Dollar Bus Service Enhancement Programme Completed with 1,000th Bus Added to Fleet*. Dec. 9, 2017. URL: https://www.todayonline.com/singapore/billion-dollar-bus-service-enhancement-programme-completed-1000th-bus-added-fleet (visited on 10/15/2018).

[50] Land Transport Authority Strategic Planning. *Public Transport Ridership*. Apr. 18, 2018. URL: https://public.tableau.com/profile/lta.strategic.planning#!/vizhome/2018Ridership_Public/PTRidershipDashboard (visited on 10/24/2018).

[51] Xue, F. and Gwee, E. 'Electric Vehicle Development in Singapore and Technical Considerations for Charging Infrastructure'. In: *Energy Procedia* 143 (Dec. 2017), pp. 3–14. ISSN: 18766102. DOI: 10.1016/j.egypro.2017.12.640.

[52] Land Transport Authority. *LTA DataMall User Guide & Documentation*. Sept. 21, 2018. URL: https://www.mytransport.sg/content/dam/datamall/datasets/LTA_DataMall_API_User_Guide.pdf.

[53] Land Transport Authority. *Certificate of Entitlement Quota for November 2017 to January 2018 and Vehicle Growth Rate from February 2018*. Oct. 23, 2017. URL: https://www.lta.gov.sg/apps/news/page.aspx?c=2&id=b010406e-6edf-4224-9cd1-928706cd6fe7 (visited on 12/04/2017).

[54] Energy Market Authority (EMA). *Monthly Peak System Demand*. Aug. 7, 2018. URL: https://www.ema.gov.sg/statistic.aspx?sta_sid=201408047htU7faVzLaZ (visited on 10/24/2018).

[55] (EMA), E. M. A. *Singapore Energy Statistics 2018*. Mar. 2018. URL: https://www.ema.gov.sg/cmsmedia/Publications_and_Statistics/Publications/SES18/Publication_Singapore_Energy_Statistics_2018.pdf (visited on 10/24/2018).

[56] Emissions & Generation Resource Integrated Database (eGRID). *eGRID Summary Tables 2016*. Feb. 15, 2018.

[57] Land Transport Authority. *Land Transport Master Plan*. 2013. URL: www.lta.gov.sg/content/dam/ltaweb/corp/PublicationsResearch/files/ReportNewsletter/LTMP2013Report.pdf (visited on 09/11/2017).

[58] Land Transport Authority and Intelligent Transport Society Singapore. *Smart Mobility 2030 - Intelligent Transport Systems Strategic Plan for Singapore*. 2014. URL: https://www.lta.gov.sg/content/dam/ltaweb/corp/RoadsMotoring/files/SmartMobility2030.pdf.

[59] EN, S. M. *Electric Buses, Charging Stations Part of Proposals in LTA's 2050 Road Map*. June 3, 2016. URL: https://www.todayonline.com/singapore/electric-buses-charging-stations-part-proposals-ltas-2050-road-map (visited on 10/25/2018).

[60] Land Transport Guru. *Electric Buses in Singapore*. Jan. 30, 2018. URL: http://landtransportguru.net/electric-buses-in-singapore/ (visited on 08/06/2018).

[61] ChannelNewsAsia. *Electric Buses to Serve Singapore Commuters from 2020*. Oct. 24, 2018. URL: https://www.channelnewsasia.com/news/singapore/electric-buses-to-serve-singapore-commuters-from-2020-lta-10859168 (visited on 10/24/2018).

[62] Land Transport Guru. *60 Electric Buses Procured by LTA*. Oct. 24, 2018. URL: https://landtransportguru.net/electric-buses-procured-by-lta/ (visited on 10/25/2018).

[63] Nanyang Technological University News. *NTU and Volvo to Jointly Develop Autonomous Electric Buses in Singapore*. 11-Jan-2018. URL: http://news.ntu.edu.sg/Pages/NewsDetail.aspx?URL=http://news.ntu.edu.sg/news/Pages/NR2018_Jan01.aspx&Guid=c8c1c88d-5617-4b34-9ae3-657e29078c2a&Category=All (visited on 10/25/2018).

[64] Amin Shah. *Look Ma, No Driver! NTU's Futuristic Buses and Where to Hitch a Ride on Them*. Apr. 2018. URL: http://www.hey.ntu.edu.sg/issue36/look-ma-no-driver-ntu-futuristic-buses-and-where-to-hitch-a-ride-on-them.html (visited on 10/25/2018).

[65] ShareTransport. *Introducing Singapore's First Full Electric 24 Seater Bus*. July 16, 2018. URL: https://www.sharetransport.sg/Media/News/Article/Introducing-Singapore's-First-Full-Electric-24-Seater-bus.

[66] Fujimoto, R.; Bock, C.; Chen, W.; Page, E., and Panchal, J. H., eds. *Research Challenges in Modeling and Simulation for Engineering Complex Systems*. Simulation Foundations, Methods and Applications. Cham: Springer International Publishing, 2017. ISBN: 978-3-319-58543-7 978-3-319-58544-4. DOI: 10.1007/978-3-319-58544-4.

[67] Andelfinger, P.; Xu, Y.; Cai, W.; Eckhoff, D., and Knoll, A. 'Fast-Forwarding Agent States to Accelerate Microscopic Traffic Simulations'. In: *Proceedings of the 2018 ACM SIGSIM Conference on Principles of Advanced Discrete Simulation - SIGSIM-PADS '18*. The 2018 ACM SIGSIM Conference. Rome, Italy: ACM Press, 2018, pp. 113–124. ISBN: 978-1-4503-5092-1. DOI: 10.1145/3200921.3200923.

[68] Zehe, D.; Knoll, A.; Nair, S., and Eckhoff, D. 'Towards CityMoS: A Coupled City-Scale Mobility Simulation Framework'. In: 5th GI/ITG KuVS Fachgespräch Inter-Vehicle Communication. Vol. CS-2017-03. Technical reports / Department Informatik. Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU), May 24, 2017, p. 26. URL: `urn:nbn:de:bvb:29-opus4-85280`.

[69] Xu, Y.; Aydt, H., and Lees, M. 'SEMSim: A Distributed Architecture for Multi-Scale Traffic Simulation'. In: *2012 ACM/IEEE/SCS 26th Workshop on Principles of Advanced and Distributed Simulation*. 2012 ACM/IEEE/SCS 26th Workshop on Principles of Advanced and Distributed Simulation (PADS). Zhangjiajie, China: IEEE, July 2012, pp. 178–180. ISBN: 978-1-4673-1797-9. DOI: `10.1109/PADS.2012.40`.

[70] Xiao, J.; Aydt, H.; Lees, M., and Knoll, A. *A Partition Based Match Making Algorithm for Taxi Sharing*. 2013.

[71] Viswanathan, V.; Zehe, D.; Ivanchev, J.; Pelzer, D.; Knoll, A., and Aydt, H. 'Simulation-Assisted Exploration of Charging Infrastructure Requirements for Electric Vehicles in Urban Environments'. In: *Journal of Computational Science* 12 (Jan. 2016), pp. 1–10. ISSN: 18777503. DOI: `10.1016/j.jocs.2015.10.012`.

[72] Bi, R.; Xiao, J.; Pelzer, D.; Ciechanowicz, D.; Eckhoff, D., and Knoll, A. 'A Simulation-Based Heuristic for City-Scale Electric Vehicle Charging Station Placement'. In: *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*. 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC). Yokohama: IEEE, Oct. 2017, pp. 1–7. ISBN: 978-1-5386-1526-3. DOI: `10.1109/ITSC.2017.8317680`.

[73] Treiber, M.; Hennecke, A., and Helbing, D. 'Microscopic Simulation of Congested Traffic'. In: *Traffic and Granular Flow '99*. Ed. by Helbing, D.; Herrmann, H. J.; Schreckenberg, M., and Wolf, D. E. Berlin, Heidelberg: Springer Berlin Heidelberg, 2000, pp. 365–376. ISBN: 978-3-642-64109-1 978-3-642-59751-0. DOI: `10.1007/978-3-642-59751-0_36`.

[74] Treiber, M. and Kesting, A. 'Modeling Lane-Changing Decisions with MOBIL'. In: *Traffic and Granular Flow '07*. Ed. by Appert-Rolland, C.; Chevoir, F.; Gondret, P.; Lassarre, S.; Lebacque, J.-P., and Schreckenberg, M. Berlin, Heidelberg: Springer Berlin Heidelberg, 2009, pp. 211–221. ISBN: 978-3-540-77073-2 978-3-540-77074-9. DOI: `10.1007/978-3-540-77074-9_19`.

[75] Holger, K. *KIA Soul EV, Ladeleistingskurve 100kW SIGNET-Ladesaeule KIA Deutschland Zentral Frankfurt Am Main*. Sept. 2016. URL: `http://cdn.goingelectric.de/forum/resources/file/31223`.

[76] Li, J.-Q. 'Transit Bus Scheduling with Limited Energy'. In: *Transportation Science* 48.4 (Nov. 2014), pp. 521–539. ISSN: 0041-1655, 1526-5447. DOI: `10.1287/trsc.2013.0468`.

[77] Nurhadi, L.; Borén, S., and Ny, H. 'A Sensitivity Analysis of Total Cost of Ownership for Electric Public Bus Transport Systems in Swedish Medium Sized Cities'. In: *Transportation Research Procedia* 3 (2014), pp. 818–827. ISSN: 23521465. DOI: 10.1016/j.trpro.2014.10.058.

[78] Lajunen, A. 'Energy Consumption and Cost-Benefit Analysis of Hybrid and Electric City Buses'. In: *Transportation Research Part C: Emerging Technologies* 38 (Jan. 2014), pp. 1–15. ISSN: 0968090X. DOI: 10.1016/j.trc.2013.10.008.

[79] Aber, J. *Electric Bus Analysis for New York City Transit.* May 2016. URL: http://www.columbia.edu/~ja3041/Electric%20Bus%20Analysis%20for%20NYC%20Transit%20by%20J%20Aber%20Columbia%20University%20-%20May%202016.pdf (visited on 11/20/2017).

[80] Lindgren, L. *Full Electrification of Lund City Bus Traffic - A Simulation Study.* 2015.

[81] Zhou, B.; Wu, Y.; Zhou, B.; Wang, R.; Ke, W.; Zhang, S., and Hao, J. 'Real-World Performance of Battery Electric Buses and Their Life-Cycle Benefits with Respect to Energy Consumption and Carbon Dioxide Emissions'. In: *Energy* 96 (Feb. 1, 2016), pp. 603–613. ISSN: 0360-5442. DOI: 10.1016/j.energy.2015.12.041.

[82] Eudy, L.; Prohaska, R.; Kelly, K., and Post, M. *Foothill Transit Battery Electric Bus Demonstration Results.* Jan. 2016.

[83] Electricity. *Cooperation for Sustainable and Attractive Public Transport - Status Report June 2016.* June 2016.

[84] Sinhuber, P.; Rohlfs, W., and Sauer, D. U. 'Study on Power and Energy Demand for Sizing the Energy Storage Systems for Electrified Local Public Transport Buses'. In: *2012 IEEE Vehicle Power and Propulsion Conference.* 2012 IEEE Vehicle Power and Propulsion Conference. Seoul, Korea: IEEE, Oct. 2012, pp. 315–320. ISBN: 978-1-4673-0954-7 978-1-4673-0953-0 978-1-4673-0952-3. DOI: 10.1109/VPPC.2012.6422680.

[85] Rogge, M.; Wollny, S., and Sauer, D. 'Fast Charging Battery Buses for the Electrification of Urban Public Transport—A Feasibility Study Focusing on Charging Infrastructure and Energy Storage Requirements'. In: *Energies* 8.5 (May 21, 2015), pp. 4587–4606. ISSN: 1996-1073. DOI: 10.3390/en8054587.

[86] Goehlich, D.; Kunith, A., and Ly, T.-A. 'Technology Assessment of an Electric Urban Bus System for Berlin'. In: *Urban Transport 2014.* Urban Transport 2014. Alvor, Portugal, May 28, 2014, pp. 137–149. DOI: 10.2495/UT140121.