Estimation of the energy demand of electric buses based on real-world data for large-scale public transport networks

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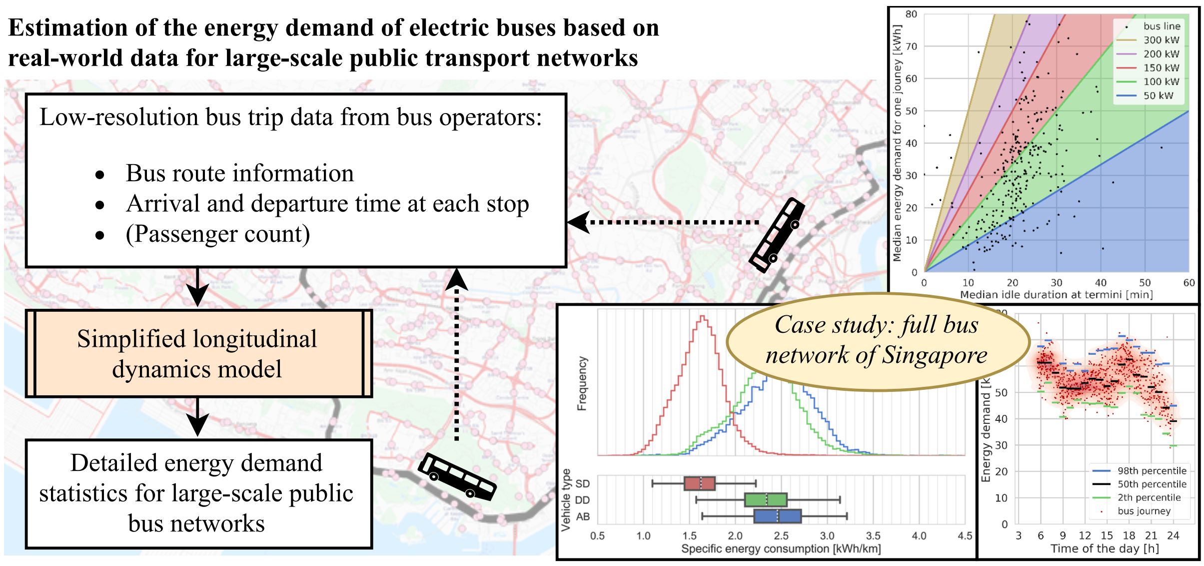
Abstract

An increasing number of cities are transitioning from fossil fuel-powered buses for public transport to battery electric buses. Evaluating the energy demand of buses has become an important prerequisite for the planning and deployment of large electric bus fleets and the required charging infrastructure. A number of state-of-the-art approaches to determining the energy requirements of electric buses use individual specific energy demand values or rely on standard driving cycles, though these do not consider local bus route characteristics. Others require high-resolution measurements of the vehicles' driving profiles, which is impractical for large bus fleets. This paper presents a longitudinal dynamics model to calculate the energy demand for electric buses. The model is designed to be easily applied to large bus networks using real data sources that are commonly available to bus transit operators. This data can be derived from low-resolution data collected from day-to-day operations, where only the arrival and departure time of the buses at each bus stop are available. This approach offers a practical alternative to state-of-the-art methods and requires no high-resolution velocity profiles, which are difficult to obtain, while still taking into account the details of the operational characteristics of the transportation network under consideration. The application of the model is demonstrated in a case study to electrify the complete public bus network in Singapore. The results showed that the heterogeneity of driving conditions observed in a large network leads to a high variance in energy requirements between different bus lines and at different times of day. This confirms the need to take the characteristics of each individual bus route into account. In the case-study, a fully electric public bus fleet would require about 1.4 GWh per day for revenue service, which is about one per cent of Singapore's daily electricity demand. Another finding is that 50 % of the bus lines require less than 40 kWh per terminus-to-terminus journey, which indicates a good potential for fast opportunity charging during layover time. The results of the model should serve as the basis for further studies into battery sizes, charging strategies and charging infrastructure requirements.

Keywords: electric buses, longitudinal dynamics model, energy demand, public transportation network, sensitivity analysis



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Acronyms

AB	articulated bus
BEB	battery electric bus
DD	double-decker bus
EV	electric vehicle
GHG	greenhouse gases
ICE	internal combustion engine
MAD	median absolute deviation
SD	single-decker bus
WTW	Well to Wheel

Nomenclature

A	cross-section area of the vehicle (m^2)
a_+	acceleration rate (m/s^2)
a_-	deceleration rate (m/s^2)
C_d	drag coefficient of the vehicle
D	distance between two consecutively visited bus stops (m)
d_0	distance travelled during the acceleration phase (m)
d_1	distance travelled during the constant speed phase (m)
d_2	distance travelled during the deceleration phase (m)
f	rolling resistance
g	gravitational acceleration (m/s^2)
Δh	elevation difference between two consecutively visited bus stops (m)
M	total mass of the vehicle including load (kg)
M_{curb}	curb mass of the vehicle including battery (without passengers) (kg)
m_{pax}	mass of a passenger (kg)
n_h	number of intermediate halts during a trip
n_{pax}	number of passengers
P_{aux}	auxiliary power (including air-conditioning) (W)
r_{reg}	regeneration factor
Δt_{dwell}	dwell time at a bus stop (s)
Δt_{trip}	trip duration between two consecutively visited bus stops (s)
v_1	coasting speed (m/s)
α	inclination angle of the road
δ	inertia factor
η_m	average efficiency of the motor
η_{PE}	average efficiency of the inverter
η_t	average efficiency of the drivetrain and gearbox
ρ	air density (kg/m^3)

1. Introduction

The continuous demographic growth in cities leads to an increase in the number of private vehicles on the streets, exacerbating road congestion and parking space scarcity issues. This is why implementing policies that favour public transport as a preferred mode of transportation is one of the priorities of policymakers to improve urban transportation. Is suitably dimensioned with regards to passenger occupancy, public transportation systems have several advantages over private vehicles: better road space usage, higher energy efficiency and lower greenhouse gases (GHG) emissions per passenger-kilometre. Nevertheless, electric mobility in public transport systems still has a long way to go because — apart from already electrified modes such as metro, trams or trolleybuses — diesel buses still constitute the majority of vehicles in urban public transport vehicle fleets.

Increased concerns about the impact of emissions from fossil-fuelled internal combustion engine (ICE) vehicles on the global environment and public health [1] as well as continuous improvements in the economic viability of electric vehicles (EVs) have lead to a growing interest in electric mobility from researchers, industry players and consumers [2]. EVs can help to alleviate a number of contemporary issues with road-bound transportation that especially affect urban environments. With no direct tailpipe emissions, they do not cause health hazards or olfactory discomfort to passengers in the immediate vicinity of the vehicle. Their heat and noise emissions are significantly lower as well. On top of that, passengers experience greater comfort due to the lack of motor vibrations [3]. From an environmental perspective, EVs are able to bring important Well to Wheel (WTW) fossil fuel savings and reduce GHG emissions [4, 5]. The continued rise of renewable energy sources in the electricity mix is further contributing to the sustainability of electric mobility on a long-term basis.

In recent years, bus operators have been showing a growing interest in the use of fully electric buses in their fleets. Numerous pilot projects are currently being rolled out in cities around the world [6–8]. With traditional diesel buses, detailed energy demand calculations were not necessary as the range of a diesel bus with a full tank exceeds the daily fuel consumption. The exact value varies with the bus model, but typical tank capacities for diesel buses vary between 200 L and 600 L. A fuel economy of between 40 L/100 km and 60 L/100 km results in a driving range from 330 km to 1500 km in the worst and best case respectively. More realistically, an average tank capacity of 300 L and fuel economy of 50 L/100 km yields an available range of 600 km, which is quite enough for a day of operation. Besides, refuelling only takes a few minutes.

The additional constraints associated with the range and charging limitations of battery electric buses (BEBs) pose a challenge for the electrification of existing bus fleets. An electric bus network requires a charging infrastructure and schedule that does not jeopardise bus operation, but is not too costly either. The complexity increases proportionate to the size of the bus network under consideration. In order to plan an electric bus network and select the right battery capacity of the BEBs, the energy demand of each bus line has to be determined over the entire day under different traffic conditions.

Previous studies mostly used one of the following three approaches to determine the energy demand for electric buses.

1. Calculation of the average energy demand per unit of distance or time

This is the simplest approach. A single value is used for the average energy demand for each bus type (e.g. single-decker or double-decker) on all routes. This approach is often used in studies focusing on BEB scheduling problems. In a case study in Penghu, Taiwan, Ke et al. [9] calculated the energy requirements of local bus lines based on the route distance and two fixed specific energy demand values for large- and medium-sized e-buses respectively. Paul and Yamada [10] used a single value for the average energy demand taken from the Ministry of Land, Japan. Similarly, Wang et al. [11] used a single value, assuming the energy demand to be proportional to the total driving distance with no variations during the day. As part of studying charging infrastructure requirements for electric buses, Xylia et al. [12] calculated the energy demand of the entire bus network in Stockholm, Sweden. This calculation was based on real trip schedules but was also assumed to be proportional to the trip distance.

Though this approach is very simple to implement, using average energy demand values only yields a rough estimate of the energy demand and does not consider traffic conditions at different times of the day or route characteristics such as ascents or descents. Moreover, it ignores the fact that the auxiliary power is constantly being drawn, mainly for air conditioning or heating. Thus, the energy demand due to the auxiliary power depends on the trip duration instead of the trip distance. During peak hours, a bus journey could take considerable longer than during off-peak hours, resulting in a much higher energy demand.

2. Use of a standard driving cycle taken from literature

In this approach, standard driving cycles are taken from literature. These driving cycles are based on traffic measurements from different cities. Examples of well-known standardised driving cycles are the Braunschweig, New York City, Orange County or Paris bus cycles. An overview of the characteristics of various driving cycles can by found in [13]. Authors of previous studies usually chose a driving cycle similar to the conditions in their study area. Vilppo and Markkula [14] examined a few standard driving cycles and then used the one which included a similar number of bus stops to the city in which their study was based. Possible differences in traffic conditions, especially during peak hours, were not considered, however. Lajunen and Lipman [4] carried out simulations in six different driving cycles. They then applied the one that best matched the bus line's characteristics to each line. A model of the energy demand of buses was derived from a standard driving cycle in [15] and used on a small network of seven bus lines.

Standard driving cycles include variations such as driving on a highway or in congested traffic. However, applying a standard driving cycle in a different city will inevitably lead to discrepancies. As in the first approach, traffic conditions on different bus routes are not identical, especially in large bus networks. Great variations can also occur between different types of bus services, e.g., feeder, trunk or express services. Nylund et al. [13] examined several driving cycles for heavy-duty vehicles including buses. They concluded that the performance of these driving cycles can differ a lot from real-life conditions, especially for bus services, since buses have a low average speed with many stops and high deceleration / acceleration before / after reaching a stop. Shen et al. [16] described how a new driving cycle can be constructed based on data collection from real operation. They also note that "constructing a typical driving cycle which can reflect the actual driving characteristics of the vehicle means a lot to the credibility of the test results". However, the steps necessary to create this adapted driving cycle are not simple and require a significant number of measurements. Moreover, this has to be repeated for each bus route.

3. Detailed measurements of driving profiles

In order to obtain more accurate values for the energy demand of buses, measurement equipment can be installed in buses to record the energy demand with a high temporal resolution. Simulation models can be derived from the results. Sinhuber et al. [17] developed a longitudinal dynamics model in a case study for a loop line in Aachen, Germany. The characteristics of the considered bus route were derived from waypoints (geocoordinates) defined via an Internet mapping service. Route characteristics such as the *stop duration* and *speed limit* were subsequently added to the defined waypoints. However, it is unclear whether this input data was added manually or if the process to generate it was automated. Moreover, the methodology to derive the actual speed profile from these "annotated" geocoordinates was not described. The vehicle model was validated with measurement data for the traction power taken from the operation of two serial hybrid buses operating on a bus line in another city. The energy demand model was then applied to a variety of bus lines from different cities in Germany. This model was later used by Rogge et al. as a preprocessing step to calculate the energy demand for bus routes in the city of Muenster, Germany in [18] and for Aachen, Germany and Roskilde, Denmark in [19]. However, the authors once again did not elaborate on how the actual speed profile used in the longitudinal dynamics model was generated. Ly et al. [20] recorded the velocity profile of a single bus line in Berlin with a GPS sensor and used it to create a similar energy demand model. The model was then validated using data gathered from two electric buses by installed equipment measuring the speed, auxiliary power and battery state of charge with a frequency of 10 Hz. The results for the commercial operation of nine electric buses on three routes in Seoul city were presented in [21]. A single driving profile was measured for each bus routes and used to calculate the energy consumption. Zhou et al. [5] expressed concerns about the representativeness of laboratory testing and test driving cycles and noted that "the test cycles may not accurately represent real-world conditions". As part of a demonstration project, they installed an onboard data collector in three models of BEBs and recorded the speed and battery power during a test on an 8.8 km route in the downtown and business centre of Macao. The energy demand of the buses was analysed under various passenger loads and driving conditions. Prohaska et al. [22] presented an evaluation of the deployment of 12 BEBs on a 26.8 km route in the San Gabriel and Pomona Valley region of Los Angeles County, California, was presented. The authors analysed various operating metrics in detail and concluded that a good understanding of the overall duty cycle of electric vehicles was important in order to determine the feasibility of their deployment. Gao et al. [23] used a large data set of second-by-second measurements from three diesel buses, in Knoxville, USA, which covered a mileage of nearly 71,500 km over 610 days. They evaluated the energy demand and charging needs of city transit electric buses in this transportation network and suggested that significant savings might be able to be achieved on the total investment cost for the batteries if the buses were to use flexible battery configurations and charging strategies depending on the individual driving characteristics of the bus routes. They also cited a number of previous field-tests in their introduction and noted that "these limited studies were conducted only under relatively simple and limited test routes, which lack complexity and variation of more extensive real-world driving conditions".

The approaches requiring field-test measurements are inherently limited with respect to their scalability: measuring the driving profile of each bus route may be manageable for small bus networks, but for larger bus networks it rapidly becomes impractical. In all of the cited studies, detailed measurements were only carried out for a few buses. This leads to the same problem of not considering all bus lines, some of which could have significantly different characteristics. And several measurements would have to be performed on each bus line to consider traffic conditions.

This paper introduces a different approach comprising an energy demand model to help bus operators plan the electrification of their existing networks. It aims specifically at overcoming situations where high-resolution data is unavailable, without resorting to oversimplified estimations that ignore real-world trip characteristics. This model for BEB fleets is based on the common longitudinal dynamics formulation. It is adapted so that it does not require high-resolution measurements of velocity profiles. All it needs are records of arrival and departure time of buses at each stop. This new approach takes into account the variety of situations encountered in real operational conditions while keeping the energy demand analysis tractable, even at the full scale of a major bus network. This is achieved by using network-wide data sets that can be easily derived from data sources commonly collected by bus operators on the basis of existing operational data records. Examples include bus fleet management systems, which record the position of each vehicle at low resolution, or fare management systems, which record alighting and boarding events for all passengers at all bus stops. The use of such data sets enables bus operators to apply the model to their existing networks as a whole and over long periods of time.

In a case study, the described model is applied to a data set from the public transport fare management system in Singapore. The public bus network in Singapore comprises more than 350 different bus lines, with over 4000 buses in operation simultaneously during peak-hours. The energy requirements that would have to be satisfied to operate an entire fleet of electric buses on todays existing bus routes are estimated. The results are visualised and analysed. The benefits of analysing their statistical distribution instead of focusing solely on average values or using standard driving cycles are highlighted. Finally, a sensitivity analysis conducted on the model helps to determine which parameters have the most influence on the energy demand estimation.

The benefits of the proposed approach are manifold. The method is easily applicable to other bus networks and overcomes a problem often encountered in practice: the unavailability of highly-detailed data sets at large scales. It bridges a methodology gap between assumptions ignoring real-world bus trip characteristics and methods requiring high-resolution data. The main contributions of this paper are:

1. Derivation of a model for the energy demand of electric buses which does not require detailed driving profiles, but takes into account the real-world bus route characteristics and is accurate enough to yield realistic results

2. Application of the model on a real data set for the entire public bus network of a megacity (Singapore)

3. Detailed analysis of the energy demand of every single bus line over an entire day of operation

The rest of this paper is organised as follows. Section 2 describes the setup of the model including the synthetic driving profile. The case study of the public bus network in Singapore is introduced in Section 3. Results and discussion are presented in Section 4. In Section 5, we show the results of the sensitivity analysis. Section 6 concludes the paper and provides a brief outlook on future work.

2. Methodology

2.1. Nomenclature

Unless otherwise stated, a *trip* denotes a "bus stop to bus stop" trip spanning one visited bus stop to the next in the following. Please note that a bus may skip some bus stops if there are no passengers boarding or alighting at these stops, so that a *trip* does not necessarily connect two consecutive bus stops along the planned route. A *journey* denotes a one-way "terminus to terminus" journey. A *terminus* is hereby defined as the starting or ending stop of a bus route. Most bus lines have two different termini (and buses drive back and forth between those), whereas loop lines start and end at the same terminus.

2.2. Energy demand model

The energy demand model presented here is based on a common longitudinal dynamics model for electric vehicles [24]. The tractive force F_{tr} is calculated as follows:

$$F_{\mathrm{tr}} = F_{\mathrm{drag}} + F_{\mathrm{roll}} + F_{\mathrm{climb}} + F_{\mathrm{inertia}} \tag{1}$$

where:

- $F_{\mathrm{drag}} = K_{\mathrm{d}}\, v^2$ is the aerodynamic drag force, with $K_{\mathrm{d}} = 0.5\,\rho\, C_{\mathrm{d}}\, A$. ρ is the mass density of air in kg/m^3, C_{d} is the drag coefficient, A is the reference frontal area of the vehicle in m^2 and v the speed of the vehicle in m/s (it is assumed that the flow velocity of the air around the vehicle is equal to the vehicle speed, i.e. wind speed is neglected).

- $F_{\text{climb}} = Mg\sin(\alpha)$ is the grade force. M is the total mass of the vehicle in kg, g is the gravitational acceleration ($9.81\,\text{m/s}^2$) and α is the gradient of the road. The elevation difference Δh and the distance D between two stops are used to calculate α, such that $\tan(\alpha) = \Delta h/D$.
- $F_{\text{roll}} = Mgf\cos(\alpha)$ is the rolling friction. f is the rolling resistance coefficient.
- $F_{\text{inertia}} = \delta Ma$ is the inertia force resulting from the change in stored kinetic energy in the vehicle (acceleration or deceleration). a is the acceleration of the vehicle. δ is a factor to take into account the inertia of all rotating components in the drivetrain (wheels, drive shaft, rotor of the motor...).

If data is available about the number of in-vehicle passengers, the total mass of the vehicle M can be calculated as the sum of the curb weight M_{curb} and the total mass of the passengers on board: $M = M_{\text{curb}} + n_{\text{pax}}\, m_{\text{pax}}$. Otherwise, an estimation of the average number of passengers can be used.

Let E_{tr} be the energy demand (or regeneration) due to the tractive force on a trip between two consecutive stops:

$$E_{\text{tr}} = \int \eta \left(K_{\text{d}} v(t)^2 + Mgf\cos(\alpha) + Mg\sin(\alpha) + \delta M a(t)\right) v(t)\,\text{d}t \tag{2}$$

where η is an efficiency factor that takes into account the losses in the inverter, motor, drivetrain including gearbox. When the vehicle is braking ($a(t) < 0$) or driving down a sufficiently inclined road ($\sin(\alpha) < 0$), the value of the tractive force can become negative. When this happens, electric vehicles are usually able to convert and store part of the kinetic energy back in the battery (regenerative braking). Thus, η needs to be calculated differently depending on whether the tractive force is positive (energy demand) or negative (energy regeneration):

$$\eta = \begin{cases} \dfrac{1}{\eta_{\text{t}}\,\eta_{\text{PE}}\,\eta_{\text{m}}} & \text{for } F_{\text{tr}}(t) \geqslant 0 \\ r_{\text{reg}}\,\eta_{\text{t}}\,\eta_{\text{PE}}\,\eta_{\text{m}} & \text{for } F_{\text{tr}}(t) < 0 \end{cases} \tag{3}$$

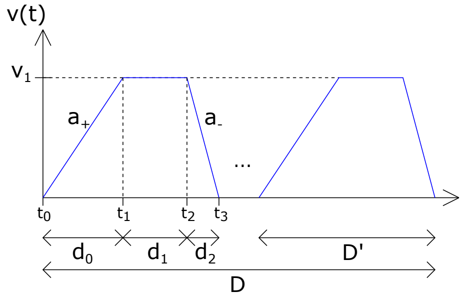
where η_{t} is the drivetrain and gearbox efficiency, η_{PE} the efficiency of the inverter and η_{m} the efficiency of the motor, and r_{reg} is the regeneration factor, which determines how much of the kinetic energy can be regenerated. This regeneration factor takes into account the fact that not all of the kinetic energy can be recovered due to losses and limitations of the maximum power for recharging the battery.

In addition to the energy related to the tractive force, the auxiliary power P_{aux} needed for air conditioning and various auxiliary services (such as operating doors, powered steering, lighting, in-vehicle displays, etc.) needs to be taken into account. In this paper, P_{aux} is assumed to be constant over the driving duration Δt_{trip} as well as the dwell time Δt_{dwell}:

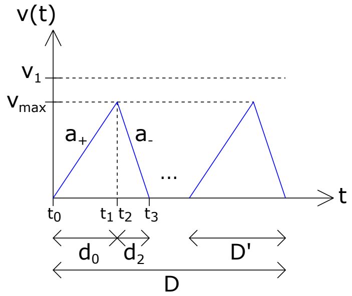
$$E_{\text{aux}} = P_{\text{aux}} \left(\Delta t_{\text{trip}} + \Delta t_{\text{dwell}}\right) \tag{4}$$

2.3. Synthetic driving profile

A synthetic driving profile that requires only the arrival and departure times of buses at all visited stops is derived in the following. This profile aims at imitating urban driving conditions, where buses often have to stop at intersections or traffic lights and go through a succession of acceleration and deceleration phases between each pair of stops. As explained in the introduction, obtaining high-resolution measurements for the driving profiles of all buses in order to calculate the integral of equation (2) is impractical in large bus networks.



(a) Case when the total distance D is long enough for the coasting speed v_1 to be reached.



(b) Case when the coasting speed is not reached because the total distance D is too short.

Figure 1: Simplified speed profile

The duration of each trip between two visited bus stops Δt_{trip} and the dwell time at each stop Δt_{dwell} is calculated from arrival and departure times. Combined with the known distance D between the stops, this yields the average speed of the trip $v_{\text{avg}} = D/\Delta t_{\text{trip}}$.

In order to better reproduce the real driving conditions to which a bus is exposed, a simplified speed profile is derived dynamically for each trip between each pair of bus stops so that it matches the available real-world data (inter-stop distance D and trip duration Δt_{trip}). It consists of a succession of $n_{\text{h}} + 1$ identical phases of the length $D' = D/(n_{\text{h}} + 1)$. n_{h} corresponds to the number of intermediate *halts* between two stops, e.g. in order to stop at a traffic light or give way at an intersection. Each phase starts with constant acceleration a_+ over distance d_0, followed by constant speed v_1 over distance d_1 and comes to a halt with constant deceleration rate a_- over distance d_2, so that $d_0 + d_1 + d_2 = D'$ (see Figure 1).

The values of n_{h} and v_1 are chosen dynamically based on the measured average speed v_{avg}. For n_{h}, it is assumed that there is at least one intermediate halt per trip, and one more for each

5 km/h-step that v_{avg} takes under 25 km/h[1]. The coasting speed v_1 is set for each trip so that $v_1 = 1.5\, v_{avg}$, but with a lower limit of 15 km/h and an upper limit defined as the maximum between v_{avg} and 60 km/h. By way of illustration, if the duration of a given trip was measured as being longer than usual (due to a higher road congestion for example), the synthetic profile will take this into account by using a lower coasting speed (v_1) and adding more intermediate halts (n_h). Inversely, if the measured trip duration was shorter than usual, then v_{avg} will be higher, as will v_1, while the number of intermediate halts is reduced.

This simplified velocity profile permits the analytical integration of Equation (2) and elimination of the time component so that E_{tr} only depends on known parameters and the trip variables from the real-world data set (D and Δt_{trip}). The integral is separated into three parts, one per phase: acceleration, coasting and deceleration. Each part is integrated on the assumption that the acceleration is constant (5).

$$\begin{aligned} E_{tr} &= (n_h + 1)\, E'_{tr} \\ &= (n_h + 1)\left(E'_{tr,\, a(t)=a_+} + E'_{tr,\, a(t)=0} + E'_{tr,\, a(t)=a_-}\right) \end{aligned} \tag{5}$$

This results in three formulas[2] (6a), (6b) and (6c).

$$E'_{tr,\, a(t)=a_+} = \eta\, d_0 \Big(Mgf\cos(\alpha) + Mg\sin(\alpha) + K_d\, a_+\, d_0 + \delta M a_+\Big) \tag{6a}$$

$$E'_{tr,\, a(t)=0} = \eta\, d_1 \Big(Mgf\cos(\alpha) + Mg\sin(\alpha) + K_d\, {v_1}^2\Big) \tag{6b}$$

$$E'_{tr,\, a(t)=a_-} = \eta\, d_2 \Big(Mgf\cos(\alpha) + Mg\sin(\alpha) - K_d\, a_-\, d_2 + \delta M a_-\Big) \tag{6c}$$

The distances d_0, d_1 and d_2 are calculated as follows: if D' is sufficiently large to reach the coasting speed (i.e. $d_1 > 0$ in (7b), see Figure 1a):

$$d_0 = \frac{v_1^2}{2\, a_+} \tag{7a}$$

$$d_1 = D' - (d_0 + d_2) = D' - \frac{{v_1}^2}{2}\left(\frac{1}{a_+} - \frac{1}{a_-}\right) \tag{7b}$$

$$d_2 = -\frac{{v_1}^2}{2\, a_-} \tag{7c}$$

otherwise (see Figure 1b):

$$d_0 = D' \frac{a_-}{a_- - a_+} \tag{7d}$$

$$d_1 = 0 \tag{7e}$$

$$d_2 = D' \frac{a_+}{a_+ - a_-} \tag{7f}$$

[1] i.e. $n_h = 1$ for $v_{avg} \geqslant 25$ km/h, $n_h = 2$ if $20 \leqslant v_{avg} < 25$ km/h, $n_h = 3$ if $15 \leqslant v_{avg} < 20$ km/h, etc.

[2] The derivation of these formulas is available in a supplementary document.

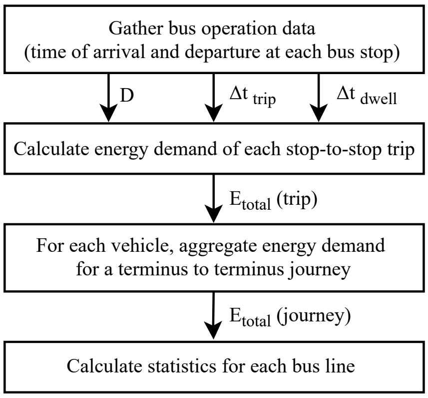


Figure 2: Overview of the steps to calculate the energy demand of a bus fleet based on operation data.

The total energy demand between two consecutive stops ($E_{total,trip}$) can finally be calculated as the sum of the energy demand for each phase plus the auxiliary energy demand (8).

$$E^{trip}_{total} = E_{tr} + E_{aux} \tag{8}$$

Consequently, the energy demand for a terminus-to-terminus journey ($E_{total,journey}$) is the sum of the energy demand of the individual stop-to-stop trips (9).

$$E^{journey}_{total} = \sum_{trip} E^{trip}_{total} \tag{9}$$

2.4. Summary of the derivation of the energy demand

Figure 2 summarises the steps taken to evaluate the energy demand of a complete bus fleet. The graph in Figure 3 illustrates how all of the required variables for the equations are derived from a small subset of input variables that can easily be obtained by operators. The required input data from real-world operation is limited to three variables:

- the distance between two consecutively visited stops (D),
- the trip duration (Δt_{trip}) and
- the dwell time (Δt_{dwell}).

The trip distance is known because the bus routes are fixed. Trip duration and dwell time are obtained directly from the recorded arrival and departure times at bus stops.

Two additional input variables from real-world measurements are also useful, but not absolutely necessary. If available, the number of passengers on board (n_{pax}) can be used to compute a better estimate of the total mass of the vehicle. Otherwise, assumptions about the average bus occupancy rate can be used to calculate M. The gradient of the road (α) between two stops also improves the accuracy of the energy demand estimation when it is known. Unless the bus network under consideration contains significant variations in elevation, the impact of this factor is limited (as is the case in Singapore).

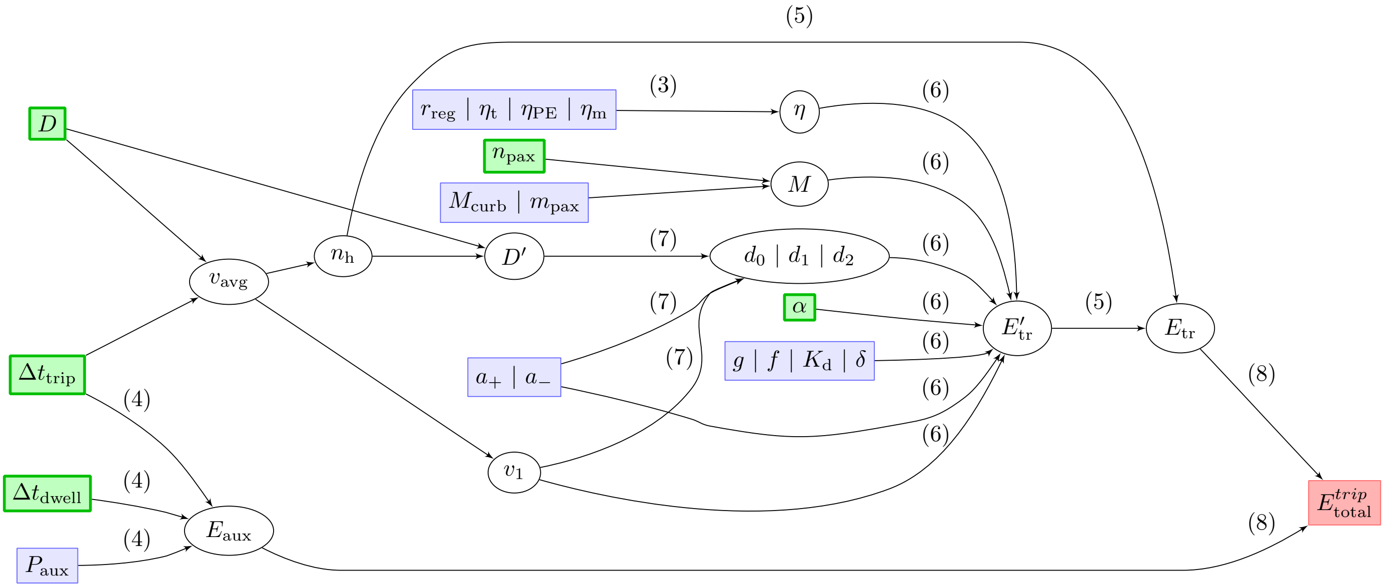


Figure 3: Graph illustrating how input data and input parameters are used to calculate the energy demand. The input data from low-resolution records of bus trips are shown inside green rectangles. The blue rectangles represent the input parameters that are static. Intermediate variables are displayed inside ellipses. The red box represents the total energy demand for one stop-to-stop trip. Numbers in parentheses along the edges correspond to the equation numbers in this paper.

3. Application of the model to a case study of Singapore

3.1. Context of the case study

Being an island city-state with limited space, it is difficult for Singapore to allow a further increase in the number of private cars. With effect from February 2018, the annual vehicle growth rate for all private passenger cars and motorcycles was set to zero (down from 0.25 % in 2017). This is enforced by a quota system, which limits the number of vehicle registrations [25]. Accordingly, current policies aim at further extending the public transport infrastructure and quality of its service in order to incite travellers to choose public transport over private vehicles. The Land Transport Master Plan 2013 [26] sets out a number of goals to be achieved by 2030, including increasing the share of journeys by public transport during peak hours from 63 % to 75 %. Similar to the trend seen in other cities, the Land Transport Authority (LTA) of Singapore is showing a growing interest in the use of hybrid and electric buses [27, 28]. In December 2017, LTA published a tender for procuring 50 hybrid electric and 60 fully electric buses for delivery in late 2019 and early 2020 [29].

Singapore's public bus network is large, with over 350 bus routes and a fleet of more than 5000 buses. Our model for the energy demand of buses is demonstrated using real-world data from this full-scale network.

3.2. Data basis

In Singapore, passengers who use public transport pay fares based on the distance travelled. Every passenger must tap their contactless card when boarding a bus and then tap it again upon alighting. The basis for this energy demand analysis is the "CEPAS" data set provided by the Land Transport Authority (LTA) of Singapore. This contains anonymised records of all tap-in and tap-out fare transactions in the public transit system over a period of three months (from August to October 2013). The data set placed at our disposal was limited to the weekdays from Mondays to Thursdays. In comparison, Fridays and weekends have a reduced ridership, lower number of active bus services and lower traffic congestion. Hence, the energy demand would be lower than in the results presented in Section 4.

The data is aggregated at the level of each individual stop-to-stop trip. Instead of one record per tap-in or tap-out event, the data set contains one record per stop at a bus stop, for each individual bus, with the aggregated sum of boarding and alighting passengers at that stop. The arrival and departure time at each bus stop, as well as the dwell time, are calculated on the basis of the time between the first and last tap-in and/or tap-out event at each stop. One example of the content of the data set is shown in Table 1. Since the data set only covers data for the passenger fare payment system, no information about *off-service* trips (also known as *dead-heading*) can be derived from it. Thus, the effect of dead-heading on the energy demand is not included in the results. It is expected to be small at the system level and could be modelled as an additional correction factor based on the ratio of dead-heading mileage to revenue service mileage.

Table 2 lists the values chosen for the constant parameters in this study. Three types of buses are operated in the public transport network of Singapore: single-decker bus (SD), double-decker bus (DD) and articulated bus (AB). Table 3 lists the values for the parameters that depend on the vehicle type (M_{curb}, A and P_{aux}). Table 4 lists the variables whose values are obtained from the "CEPAS" data set and change for each individual stop-to-stop trip. In order to calculate the road gradient α, the elevation difference between two consecutively visited stops (Δh) was derived from NASA's Shuttle Radar Topography Mission (SRTM) data [30]. In Table 2 and 3, the values were

Table 1: Excerpt of the input data for the first 5 stops visited during a journey on bus line 100.

Current stop number		11009	11189	11179	11169	11049	...
Arrival time		15:33:01	15:35:34	15:36:55	15:38:02	15:41:25	...
Passengers boarding		7	1	2	11	0	...
Passengers alighting		0	1	0	4	4	...
Delta passengers		7	0	2	7	−4	...
In-vehicle passengers	n_{pax}	7	7	9	16	12	...
Dwell time	Δt_{dwell}	00:00:27	00:00:07	00:00:08	00:00:24	00:00:22	...
Departure time		15:33:28	15:35:41	15:37:03	15:38:26	15:41:47	...
Next stop number		11189	11179	11169	11049	11039	...
Trip distance (m)	D	662	236	600	948	384	...
Trip duration	Δt_{trip}	00:02:06	00:01:14	00:00:59	00:02:59	00:01:09	...
Average trip speed (km/h)	v_{avg}	18.9	11.5	36.6	19.1	20.0	...
Vehicle type		SD	SD	SD	SD	SD	...

Table 2: Constant parameters used in the case study

Parameter	Value	Unit
C_d	0.7	–
ρ	1.18	kg/m^3
f	0.008	–
η_t	0.97	–
η_{PE}	0.95	–
η_m	0.91	–
δ	1.1	–
r_{reg}	0.6	–
m_{pax}	75	kg
a_+	1	m/s^2
a_-	−1.5	m/s^2

Table 3: Parameters used in this case study depending on vehicle type

Parameter	Vehicle type			Unit
	SD	DD	AB	
M_{curb}	12.5	17.5	18.5	t
A	8.3	10.35	8.3	m^2
P_{aux}	10	15	15	kW

chosen so that they are indicative of typical parameter values found in literature.

4. Results and discussion

4.1. General statistics for the bus fleet

The results in this section are based on a four-day subset of the original data set from 26 to 29 August, 2013. It consists of 4.9 million bus stop to bus stop trips, representing 163,826 terminus to terminus journeys by 350 different bus lines and 4135 different buses over a total mileage of more than 3 million km. Applying the model introduced in Section 2.2 to this data

Table 4: Variables derived from the data set

Variable	Description
D	Distance between two consecutively visited stops
Δt_{trip}	Duration of a stop-to-stop trip
Δt_{dwell}	Dwell time at a stop
v_{avg}	Average speed during the stop-to-stop trip
n_{pax}	Number of passengers on the bus
Δh	Difference in elevation between two consecutively visited stops
Vehicle type	Type of the vehicle (SD, DD, AB)

set results in an identically-sized data set containing the energy demand for each of these 4.9 million stop-to-stop trips. Thereafter, the data is aggregated at the level of bus journeys, then at the level of bus lines and finally at the system level.

Based on this historical data set, a fleet of electric public buses in Singapore would require about 1.4 GWh (5 TJ) in total per day for revenue service, or 1.9 kWh/km on average (including all vehicle types). Taking into account the number of passengers on the bus for each trip, the median efficiency is 101 Wh (364 kJ) per passenger-kilometre. This hypothetical energy demand represents about one percent of the current average daily total electricity consumption of Singapore, which amounted to 133 GWh per day in 2016 [31]. Since no statistics are available on the total energy consumption of the current public bus fleet in Singapore, a direct comparison of the results with the current diesel bus population is not possible. However, it can be assumed that a typical single-decker diesel city bus in an urban driving cycle has an average fuel efficiency of around 40 to 50 L/100 km (including air conditioning and subject to driving conditions), corresponding to 4 to 5 kWh/km [32–34]. Compared with electric buses, diesel buses thus consume between two and three times more energy. This is mostly due to the lower efficiency of heat engines and the lack of energy regeneration capabilities. For example, Nylund et al. [33] measured the fuel economy of various diesel bus models and compared it to the mechanical work actually performed (measured by a dynamometer). They found that whereas diesel engine manufacturers report efficiencies up to 45 %, the measured efficiency on urban driving cycles was between 21 % and 26 %. In comparison, this case study assumes that the electric motor has an average efficiency of 91 %, and can regenerate about 60 % of the braking energy.

Table 5 summarises the results aggregated at the level of terminus-to-terminus journeys. The share of total distance driven and the number of buses for the three main types of vehicles are provided to indicate the relative contribution of each vehicle type to the results. About two thirds of the total mileage were covered by single-decker buses, one quarter by double-decker buses and the rest by articulated buses. The median values (outside parentheses) obtained by the model for the specific energy demand are 1.6 kWh/km, 2.3 kWh/km and 2.5 kWh/km for single-decker, double-decker and articulated buses respectively. The values of the median absolute deviation (MAD) are shown in parentheses. The median value of the total energy demand for a terminus-to-terminus journey ranges from 28.7 kWh to 45.0 kWh, depending on the vehicle type. Table 6 shows the daily mileage and energy demand per bus. The median value of the daily distance driven per bus is 186 km with a median energy demand of 336 kWh.

4.2. Discussion of the variability observed in real-world bus networks

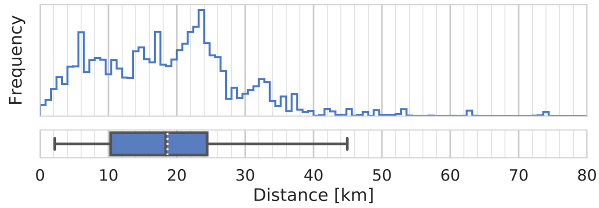
The values presented in Tables 5 and 6 have high variances, as can be seen from the median absolute deviation (MAD) shown in parentheses. This is due to the nature of large public bus networks such as Singapore's, which are inherently heterogeneous. Real conditions of operation vary a lot between bus lines: some lines are more than 30 km long, while others cover routes of just a few kilometres; some ply routes in the city centre whereas others include motorway sections, etc. Moreover, a given bus line exhibits variations over the day: During morning and evening peak hours, more passengers are boarding and alighting, leading to prolonged dwell times at stops. Peak-hour road traffic also leads to an increase in the trip duration between stops.

For these reasons, estimating the characteristics and requirements of a bus network solely by means of average or median values is inaccurate. A single value cannot accurately reflect the high variability of real-world situations. A workaround could be to use extreme values (worst-case scenario). This is not an ideal solution either, because a small number of extreme cases from real operation will significantly skew the results. Hence, if the probability of occurrence of extreme values is not properly analysed, this approach may lead to over-sizing the system.

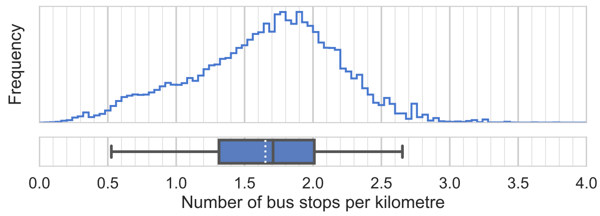
In the following subsection, we will elaborate on the characteristics of the public bus routes in Singapore and how these high variations came about in more details.

4.3. Characteristics of the bus routes

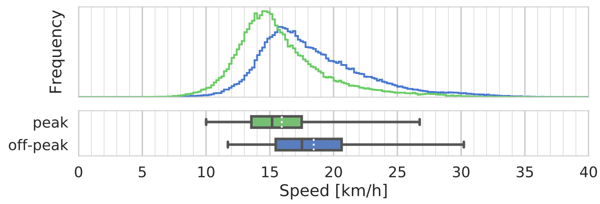
Figure 4 illustrates the variance for the characteristics of the public bus routes in Singapore. The distribution of the distance travelled on a terminus-to-terminus journey is shown in Figure 4a. The median value is 18.4 km, but the distribution is



(a) Distance travelled



(b) Number of bus stops per kilometre



(c) Average speed for peak and off-peak hours

Figure 4: Distribution of key characteristics for the bus routes per bus journey (terminus to terminus). (Box plot whiskers set at 2nd and 98th percentiles)

quite wide with a median absolute deviation (MAD) of 10 km. Excluding outliers, the 2nd and 98th percentiles of the distribution are 2 km and 45 km respectively. By way of reference, the main island of Singapore measures 50 km from west to east and 27 km from north to south.

The number of bus stops per kilometre (Figure 4b) influences the average speed and the overall energy demand of buses. On a route with a high number of stops per kilometre, the frequency of energy-intensive acceleration phases increases, as does the share of idle time, thus increasing the auxiliary energy demand. The median value for the data set amounts to 1.7 stops per kilometre (corresponding to a median distance of 588 m between two consecutively visited stops) with a MAD of 0.5.

The average speed of the bus on a journey (Figure 4c) depends on the traffic conditions throughout the day (such as peak and off-peak hours) and on whether the route passes through sections of the road network which are more likely to be congested than others. The median values of the data set are 17.5 km/h and 15.2 km/h, with a MAD of 3.6 km/h and 2.8 km/h during *off-peak* and *peak* hours respectively.

The graphs in Figure 4 clearly show the heterogeneity of real-world bus routes and high variations in their characteristics that lead to a noticeable variability of the energy demand. This underlines the necessity of using a more sophisticated approach that takes these characteristics into account when calculating the energy demand.

Table 5: Driving statistics for terminus-to-terminus journeys (median value with median absolute deviation shown in parentheses)

	Vehicle type			
	All	SD	DD	AB
Number of buses in the data set	4135	2683	1149	303
Share of total distance driven	100 %	68 %	25 %	7 %
Share of total energy demand	100 %	59 %	32 %	9 %
Distance per journey (km)	18.4 (10.4)	18.4 (10.6)	20.5 (8.8)	14.4 (10.3)
Speed (km/h)	16.7 (3.5)	16.7 (3.7)	16.6 (3.2)	16.4 (3.3)
Specific energy demand (kWh/km)	1.75 (0.41)	1.62 (0.24)	2.34 (0.34)	2.47 (0.38)
Total energy demand per journey (kWh)	32.2 (19.2)	28.7 (16.6)	45.0 (21.4)	34.2 (20.7)

Table 6: Driving statistics per bus for one day of operation (median value with median absolute deviation shown in parentheses)

	Vehicle type			
	All	SD	DD	AB
Daily mileage (km)	186 (67)	194 (67)	169 (68)	172 (65)
Total energy demand per day (kWh)	336 (120)	315 (106)	401 (161)	408 (153)

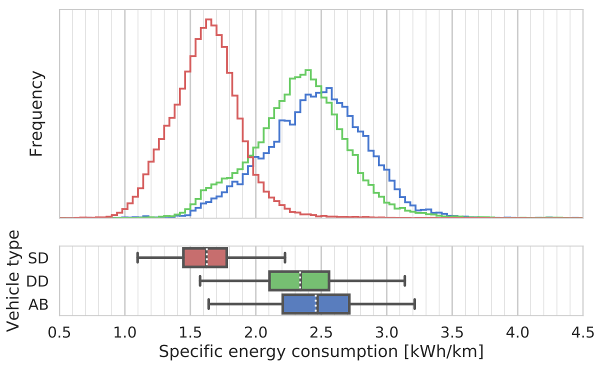


Figure 5: Distribution of the specific energy demand averaged over a journey (terminus to terminus) by vehicle type. (Box plot whiskers set at 2nd and 98th percentiles)

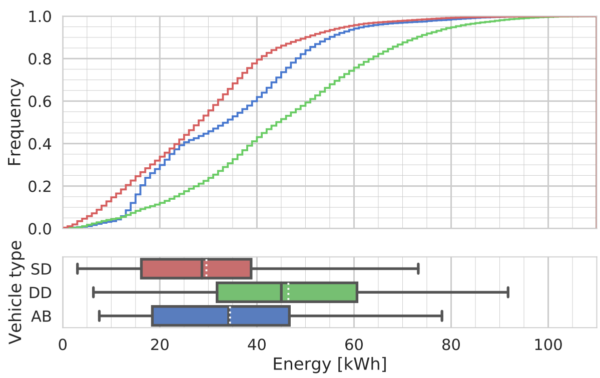
4.4. Energy demand of the electric bus fleet

This subsection presents the specific energy demand of all bus types, the energy demand per journey and day, and aggregated per bus line.

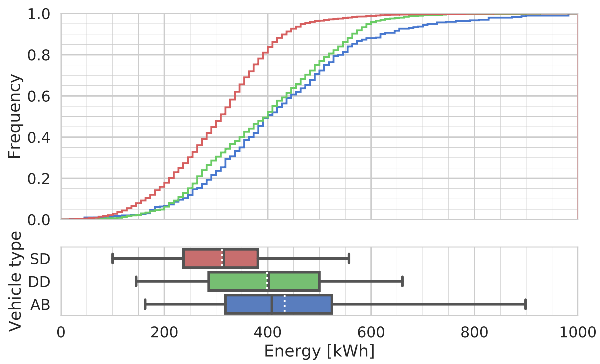
4.4.1. Specific energy demand

Figure 5 shows the distribution of the specific energy demand categorised by vehicle type. The dispersion of the values is a consequence of the variety of bus routes and driving conditions, as shown in the previous subsection. The specific energy demand obtained in our model ranges from 1.1 to 2.2 kWh/km, with a median value of 1.6 kWh/km for single-decker buses. For double-decker and articulated buses, the range is 1.6 to 3.2 kWh/km, with a median value of 2.3 kWh/km and 2.5 kWh/km respectively.

In comparison, measurements during on-road testing of two models of 12 m electric buses in Macao under various passenger loads and with air conditioning switched on resulted in average specific energy demand values ranging from 1.62 to 2.11 kWh/km in [5]. Gao et al. [23] reported simulated values ranging from 1.24 to 2.48 kWh/km for an electric bus model with characteristics similar to those of our single-decker model and using four standardised driving cycles. For heavier bus models (DD and AB), values ranging from 2.1 to 3.4 kWh/km were obtained in [17] for articulated city buses with a length of 18 m using a detailed longitudinal dynamics model on five routes in Aachen and Muenster, Germany. In [18], simulations using the bus network of Muenster, Germany, for an articulated bus model resulted in specific energy demand values ranging from 2.26 to 2.69 kWh/km, with an average of 2.47 kWh/km. These values are consistent with the distribution observed in our results and suggest that the simplified model presented in this work is able to provide results similar to those that could be obtained with a more detailed model using high-resolution velocity profiles.



(a) Per journey (terminus to terminus)



(b) Per day of operation

Figure 6: Cumulative distribution of the energy demand by vehicle type. (Box plot whiskers set at 2nd and 98th percentiles)

4.4.2. Energy demand per journey

Figure 6 shows the cumulative distribution of the energy required for a terminus-to-terminus journey (6a) and for a day of operation (6b). This representation easily allows quantitative statements to be made on the share of journeys that can be covered with a given energy amount, or conversely, the energy required to cover a given percentage of journeys to be determined. For example, Figure 6a shows that approximately 80 % of the journeys require less than 41 kWh for single-decker buses, 49 kWh for articulated buses, and 64 kWh for double-decker buses.

To put these amounts of energy in context, with fast charging stations at the end of the bus routes, the time needed to recharge these amounts of energy at a charging power of 400 kW would be less than 6 min, 7.5 min and 10 min respectively. This result suggests that the current layover time of buses at bus termini could be used to recharge the energy spent on the previous journey in most cases.

4.4.3. Energy demand per day

Another important metric is the accumulated energy used by a bus to cover all of its journeys in one day of operation. This metric can be used to determine the battery capacity of the BEBs when the charging strategy consists of overnight charging at depots only. The cumulative distribution of the daily energy demand for each vehicle type is shown in Figure 6b. The range of values is quite large. On current operational schedules and routes, single-decker BEBs would require 100 to 550 kWh (median: 315 kWh), and double-deckers 150 to 650 kWh (median: slightly over 400 kWh) per day. Some articulated buses (less than 10 % or about 30 buses) require more than 600 kWh and up to 900 kWh per day. These buses are operated on small feeder loop lines, but with very long driving times and low driving speeds on average, which explains the high energy demand.

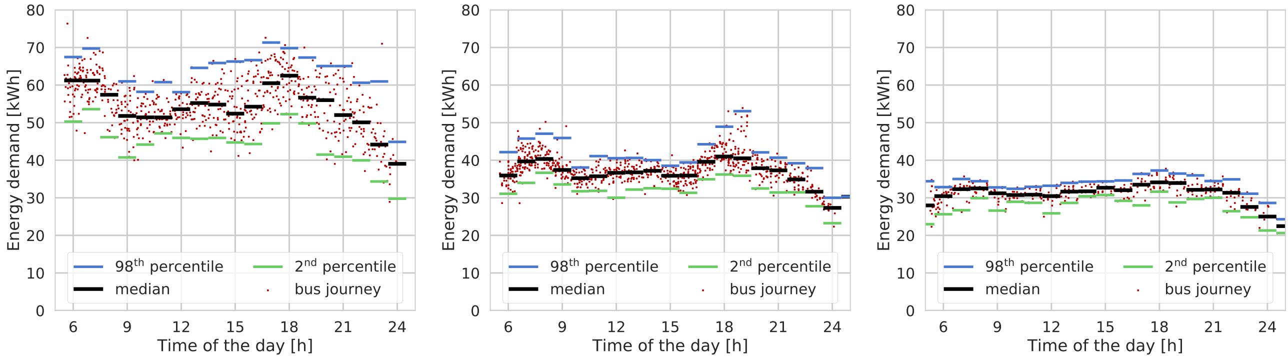
Considering these daily energy demand values, choosing overnight charging as a charging strategy would require equipping BEB with very large batteries. This would most likely be costly and more inefficient due to the added mass disadvantage compared to opportunity charging.

4.4.4. Energy demand aggregated by bus line

The previous results focused on the energy demand at the level of individual vehicles only. Any given bus line is served by a number of buses with different types of vehicle, drivers and traffic conditions. Hence, the amount of energy required can vary significantly over time. Variations between different bus lines are also significant.

To better understand the energy requirements of each bus line, the data previously calculated for each vehicle was grouped and aggregated by line number. In the following, we show how this aggregation provides detailed insights into the energy demand patterns of bus lines, and how this helps to identify which lines would be better suited for electrification and which ones could pose more challenges.

Figure 7 compares the daily energy demand patterns of three bus lines. Line 961 (Figure 7a), is characterised by a higher energy demand during peak hours (around 7 a.m. for the morning



(a) Bus line 961 (b) Bus line 100 (c) Bus line 112

Figure 7: Energy demand of single-decker buses for a terminus-to-terminus journey for bus lines 961, 100 and 112 over the day, with hourly statistics. The hourly median energy demand is depicted by black bars, while the 2nd and 98th percentiles are represented by green and blue bars respectively.

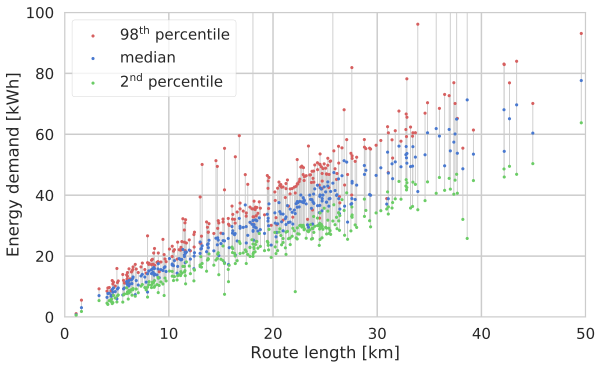


Figure 8: Energy demand for a terminus-to-terminus journey aggregated by bus line. Each bus line is represented by three points representing the median (blue), 2nd percentile (green) and 98th percentile (red) of the energy demand values observed for this line.

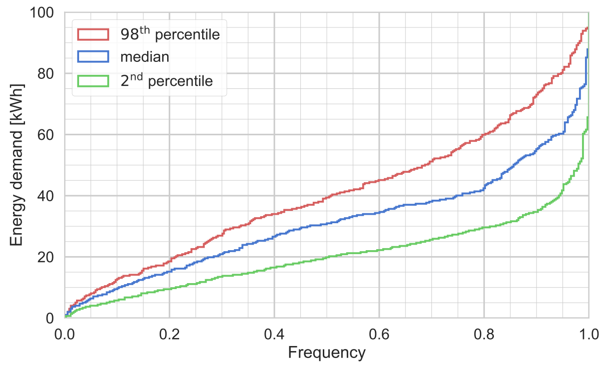


Figure 9: Cumulative distribution of the median, 2nd and 98th percentile values of the energy demand for a terminus-to-terminus journey aggregated by bus line.

peak and 6 p.m. for the evening peak) due to high numbers of passengers (increasing the mass of the vehicle) and increased road congestion. Conversely, the energy demand is below average in the evening (after 9 p.m.) as both the number of passengers and the traffic on the road are reduced. The hourly median energy demand for this line varies between 39 kWh near midnight and 62 kWh at 6 p.m., representing a variation of −29 % and +13 % around the daily median value (55 kWh) respectively. The spread between the best and worst case (in green and blue) is even more important. Most lines follow a similar pattern but with different levels of variation over the day (changes of the median value) or variance for a given time of day (spread between best and worst case). Line 100 (Figure 7c) also shows an increased energy demand during peak hours, but with a lower variance. In comparison, line 112 (Figure 7c) shows a more constant median energy demand over the day with an even lower variance than Line 100.

Figure 8 shows the median, 2nd and 98th percentiles of the energy demand values observed for each bus line are shown as a function of the route length. The energy demand appears to be roughly proportional to the distance driven, but each line shows significant variability. This confirms the fact that a consideration of the route length alone is not sufficient to accurately predict the energy required to operate an electric bus line.

Figure 9 shows the cumulative distribution of the values shown in Figure 8. This graph provides quantitative insights into the percentage of bus lines whose energy requirements per journey are less than a given value. In the worst case (red curve), for example, around 50 % of the bus lines (representing roughly 175 lines) require less than 40 kWh for one terminus-to-terminus journey, and 80 % require less than 60 kWh. This amount of energy could be recharged in less than 6 min (respectively 9 min) if 400 kW charging power were available at the bus terminus. An overview of key values from this graph is provided in Table 7.

Figure 10 provides a practical example of how the results can be further analysed to identify which bus lines have the best potential for electrification and which ones will pose the greater challenges. It could be used by bus operators and authorities to set up a roadmap for the electrification of the bus network. Since the arrival and departure time at bus stops and termini of each bus is known from the data set, it is easy to calculate how long each bus stays inside the termini before departing for another journey. In Figure 10, the median energy demand is compared with the median idle time of buses for each bus line. The

Table 7: Energy requirements for a terminus-to-terminus journey for a given cumulative percentage of bus lines. For example, 25 % of the bus lines have a median energy demand lower than 18 kWh.

Cumulative percentage of bus lines	Energy demand per journey	
	median	98^{th} percentile
25 %	≤ 18 kWh	≤ 23 kWh
50 %	≤ 31 kWh	≤ 40 kWh
75 %	≤ 40 kWh	≤ 52 kWh
95 %	≤ 60 kWh	≤ 80 kWh
100 %	≤ 88 kWh	≤ 95 kWh

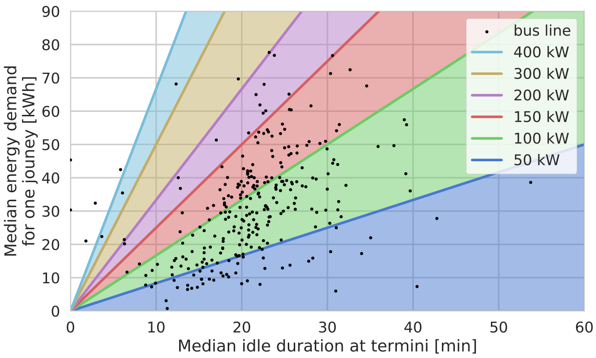


Figure 10: Median energy demand for one journey compared to the median idle time at the terminus per bus line. Each black dot represents one bus line in Singapore. The coloured areas indicate the zones where the energy spent on a journey can be recharged at a given charging power level during the idle time. For example, if a charging power of 50 kW is available, bus lines inside the blue area in the lower right could recharge during their layover time.

Table 8: Parameters for the sensitivity analysis

Parameter	Low	Base	High	Unit
M_{curb}	10	12.5	15	t
P_{aux}	8	10	12	kW
f	0.006	0.008	0.010	–
r_{reg}	0.5	0.6	0.7	–
a_+	0.7	1	2	m/s^2
a_-	−1	−1.5	−2.5	m/s^2
δ	1.07	1.10	1.13	–
C_d	0.6	0.7	0.8	–
m_{pax}	70	75	80	kg

coloured areas indicate the zones where the energy spent on a journey can be recharged during the idle time at a given charging power level. For example, if a charging power of 50 kW is available, bus lines inside the blue area in the lower right could recharge during their layover time (on average). The bus lines inside the green area, however, would require at least 50 kW and up to 100 kW of charging power to fully compensate the energy spent on their route during layover time. The closer a bus line is to the upper left corner, the harder it becomes to use opportunity charging for this bus line with current bus schedules. Following the introduction of BEBs, bus operators are expected to adjust trip schedules to allow for enough time for recharging.

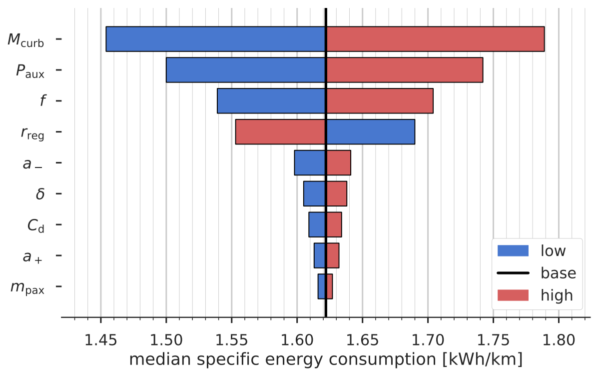
5. Sensitivity analysis

Comparing the results with existing literature is difficult because each publication uses slightly different bus models, assumptions and values for the constants. In this section, a sensitivity analysis is performed on our model to gain a better understanding of how and why our results may differ from those presented by other researchers and to identify which parameters have the greatest influence on the results.

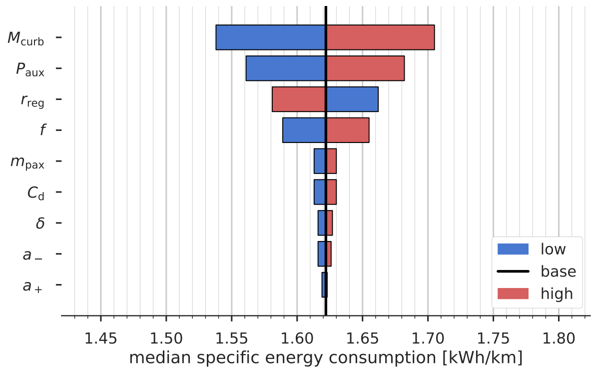
For the sake of brevity, this analysis is limited to the sensitivity of the median specific energy demand per journey for a single-decker bus. The “base” case corresponds to the parameter and results from previous sections (see Table 2 and 3). Table 8 lists “high” and “low” values for each parameter that were chosen as being representative of a typical range of values that can be found in literature. The results are shown in the form of a tornado plot in Figure 11a. Additionally, a second sensitivity analysis was performed with a variation of ±10 % from the “base” value for each parameter (Figure 11b).

From the results, it can be concluded that the parameters with the greatest influence on the energy demand estimation are, in decreasing order: the curb mass M_{curb}, the auxiliary power P_{aux}, the rolling resistance factor f and the regeneration factor r_{reg}.

The great influence of the mass is obvious and to be expected. The impact of the auxiliary power too is already well-known (see for example [5], [24, Figure 7b] and [35, Figure 6]) and confirms the importance of taking air conditioning into consideration when evaluating the energy requirements of BEBs. Nor



(a) Parameter variation according to Table 8



(b) Parameter variation: ±10 % from the “base” value for each parameter

Figure 11: Tornado plots of the sensitivity analysis for the median specific energy demand per journey.

should the value chosen for the rolling resistance constant f, whose impact is largely predominant over aerodynamic drag at the low speeds at which city buses operate, be underestimated. Other energy demand studies often assume values of either 0.01 [23, 24, 36] or 0.008 [20, 37], whereas literature on friction losses for heavy-duty vehicles suggests that 0.008 is more in an upper range, with lower limits closer to 0.004 or 0.005 [38][39, page 83]. The value of 0.008 chosen in our study is thus a conservative choice. Finally and as anticipated, the value for the regeneration factor r_{reg} has a noticeable effect on the energy demand results too. Whereas literature on energy regeneration factors for electric cars is relatively easy to find, this is not the case for heavy-duty EVs. In [40], simulations based on two driving cycles for an electric bus resulted in regenerative braking efficiency factors ranging from 0.57 to 0.67. It is still unclear which level of regenerative efficiency can be achieved in real conditions by electric city buses. The remaining parameters have little effect on the results compared to the four mentioned above.

As described in Section 2.2, the difference in elevation between each pair of bus stops (Δh) was included in our energy demand calculation. To assess the importance of this aspect in the results, the model was run again with $\Delta h = 0$ for all trips. In the Singapore case study, the influence was negligible (difference of less than 0.01 kWh/km on the median specific energy demand), which can be explained by the fact that Singapore is a very flat country (95 % of the bus stop elevations are between 7 m and 37 m). Nevertheless, road gradients in other cities can have a significant impact and should be taken into consideration when evaluating EV energy requirements.

6. Conclusion and future work

Planning the introduction of electric buses in existing public transport networks calls for careful consideration, including, but not limited to: deciding which bus lines to electrify, choosing an electric bus model and its battery capacity as well as the charging strategy (opportunity charging versus overnight charging, for example). The first step for all of these considerations is estimating the energy required to operate the existing bus lines with electric buses. In large transportation networks, this can be challenging to do in practice due to the lack of readily available data describing the detailed driving profiles of each bus route.

In this paper, a simplified longitudinal dynamics model was introduced, which overcomes this issue while facilitating the use of existing real network-wide data sets. Unlike previous approaches, which either oversimplify the estimation, or require high-resolution driving profiles, the model presented here only requires information about the bus arrival and departure times at each bus stop. This allows bus operators to use commonly available data sources to estimate the energy requirements of electric buses in their existing bus networks. Examples of such data sources include low-resolution location records from a fleet management system or data from the fare payment system, which records when and where buses stop in order to pick up or drop off passengers. By using real, large-scale data sets, this approach encourages an analysis of the statistical distribution of observed values instead of focusing on single numeric values (usually averages). This enables more realistic insights into the energy requirements of the bus network.

The model presented here was applied to a case study based on a real data set covering the entire bus network of Singapore. To the best of our knowledge, this is the first time that a detailed, network-wide estimation of the energy demand of BEBs in a large bus network of a megacity was performed on the basis of real-world trip data.

It could be shown that despite using simplified velocity profiles, the proposed model yielded plausible and highly detailed energy estimates that could be analysed in a variety of ways. In the case study, a fully electric public bus fleet operating on current bus routes would require about 1.4 GWh per day for revenue service, which is about one percent of Singapore's daily electricity demand. The daily energy demand pattern for each bus line was derived from the results. This information helps to better understand the impact of varying driving conditions on the energy demand of a bus line over the course of the day. The results displayed a significant level of heterogeneity in the energy requirements of various bus types and bus lines, even for similar route lengths. This corroborates the necessity of analysing the energy demand for each bus line individually on the basis of real-world data.

Another example of a practical application of our approach was classifying bus lines relative to their electrification potential with opportunity charging at termini. This can be used by bus operators to prioritize the electrification of the lines with the greatest potential. It was discovered that half of the existing bus lines require less than 40 kWh per terminus-to-terminus journey in the worst case, and less than 31 kWh in the median case. With fast charging capabilities becoming more widespread, this represents only a few minutes of charging time. Thus, opportunity charging at lines termini during layover time appears feasible for a large number of existing bus lines.

Many other factors affect the feasibility of electric bus operation and conclusions cannot be drawn solely on the energy demand calculation. The focus of this study was to model the energy requirements of large bus networks. However, this is only the first step in planning the deployment of electric buses. The findings from this analysis will be included in future work to determine the necessary battery capacity, to design optimized recharging strategies and to derive the charging infrastructure requirements for electric buses in Singapore's public transport network. Furthermore, the charging profiles resulting from these upcoming studies will be used to analyse the impact of the deployment of electric buses on Singapore's electric grid.

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References

[1] J. Lu, Environmental Effects of Vehicle Exhausts, Global and Local Effects : A Comparison between Gasoline and Diesel, Student thesis, Halmstad University, School of Business and Engineering (SET), 2011.

[2] M. Dijk, R. J. Orsato, R. Kemp, The emergence of an electric mobility trajectory, Energy Policy 52 (2013) 135–145. [DOI: 10.1016/j.enpol.2012.04.024].

[3] D. Honnery, R. Napper, I. Fridman, P. Moriarty, Spatially differentiated energy and environment comparison of diesel and electric buses, in: 38th Australasian Transport Research Forum (ATRF 2016), Melbourne, Australia.

[4] A. Lajunen, T. Lipman, Lifecycle cost assessment and carbon dioxide emissions of diesel, natural gas, hybrid electric, fuel cell hybrid and electric transit buses, Energy 106 (2016) 329–342. [DOI: 10.1016/j.energy.2016.03.075].

[5] B. Zhou, Y. Wu, B. Zhou, R. Wang, W. Ke, S. Zhang, J. Hao, Real-world performance of battery electric buses and their life-cycle benefits with respect to energy consumption and carbon dioxide emissions, Energy 96 (2016) 603–613. [DOI: 10.1016/j.energy.2015.12.041].

[6] J.-Q. Li, Battery-electric transit bus developments and operations: A review, International Journal of Sustainable Transportation 10 (2016) 157–169. [DOI: 10.1080/15568318.2013.872737].

[7] Union Internationale des Transports Publics, ZeEUS eBus Report, http://zeeus.eu/uploads/publications/documents/zeeus-ebus-report-internet.pdf, 2016. (accessed 2017-10-19).

[8] Global Green Growth Institute, Center for Study of Science, Technology and Policy, Electric Buses in India: Technology, Policy and Benefits, http://www.cstep.in/uploads/default/files/publications/stuff/CSTEP_Electric_Buses_in_India_Report_2016.pdf, 2016. (accessed 2017-06-20).

[9] B.-R. Ke, C.-Y. Chung, Y.-C. Chen, Minimizing the costs of constructing an all plug-in electric bus transportation system: A case study in Penghu, Applied Energy 177 (2016) 649–660. [DOI: 10.1016/j.apenergy.2016.05.152].

[10] T. Paul, H. Yamada, Operation and charging scheduling of electric buses in a city bus route network, in: 2014 IEEE 17th International Conference on Intelligent Transportation Systems (ITSC), IEEE, Qingdao, China, 2014, pp. 2780–2786. [DOI: 10.1109/ITSC.2014.6958135].

[11] Y. Wang, Y. Huang, J. Xu, N. Barclay, Optimal recharging scheduling for urban electric buses: A case study in Davis, Transportation Research Part E: Logistics and Transportation Review 100 (2017) 115–132. [DOI: 10.1016/j.tre.2017.01.001].

[12] M. Xylia, S. Leduc, P. Patrizio, F. Kraxner, S. Silveira, Locating charging infrastructure for electric buses in Stockholm, Transportation Research Part C: Emerging Technologies 78 (2017) 183–200. [DOI: 10.1016/j.trc.2017.03.005].

[13] N.-O. Nylund, K. Erkkilä, N. Clark, G. Rideout, Evaluation of duty cycles for heavy-duty urban vehicles, Final report of IEA AMF Annex XXIX (2007).

[14] O. Vilppo, J. Markkula, Feasibility of electric buses in public transport, in: EVS28 28th International Electric Vehicle Symposium and Exhibition, KINTEX, Goyang, Korea.

[15] G. De Filippo, V. Marano, R. Sioshansi, Simulation of an electric transportation system at The Ohio State University, Applied Energy 113 (2014) 1686–1691. [DOI: 10.1016/j.apenergy.2013.09.011].

[16] P. Shen, Z. Zhao, J. Li, X. Zhan, Development of a typical driving cycle for an intra-city hybrid electric bus with a fixed route, Transportation Research Part D: Transport and Environment 59 (2018) 346–360. [DOI: 10.1016/j.trd.2018.01.032].

[17] P. Sinhuber, W. Rohlfs, D. U. Sauer, 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, IEEE, Seoul, Korea, 2012, pp. 315–320. [DOI: 10.1109/VPPC.2012.6422680].

[18] M. Rogge, S. Wollny, D. Sauer, Fast Charging Battery Buses for the Electrification of Urban Public Transport—A Feasibility Study Focusing on Charging Infrastructure and Energy Storage Requirements, Energies 8 (2015) 4587–4606. [DOI: 10.3390/en8054587].

[19] M. Rogge, E. van der Hurk, A. Larsen, D. U. Sauer, Electric bus fleet size and mix problem with optimization of charg-

ing infrastructure, Applied Energy 211 (2018) 282–295. [DOI: 10.1016/j.apenergy.2017.11.051].
[20] T.-A. Ly, D. Goehlich, L. Heide, Assessment of the Interaction of Charging System and Battery Technology for the Use in Urban Battery Electric Bus Systems, in: 2016 IEEE Vehicle Power and Propulsion Conference (VPPC), IEEE, 2016, pp. 1–6. [DOI: 10.1109/VPPC.2016.7791621].
[21] U.-D. Choi, H.-K. Jeong, S.-K. Jeong, Commercial operation of ultra low floor electric bus for Seoul city route, in: 2012 IEEE Vehicle Power and Propulsion Conference (VPPC), IEEE, 2012, pp. 1128–1133. [DOI: 10.1109/VPPC.2012.6422619].
[22] R. Prohaska, K. Kelly, L. Eudy, Fast charge battery electric transit bus in-use fleet evaluation, in: 2016 IEEE Transportation Electrification Conference and Expo (ITEC), IEEE, Dearborn, MI, USA, 2016, pp. 1–6. [DOI: 10.1109/ITEC.2016.7520220].
[23] Z. Gao, Z. Lin, T. J. LaClair, C. Liu, J.-M. Li, A. K. Birky, J. Ward, Battery capacity and recharging needs for electric buses in city transit service, Energy 122 (2017) 588–600. [DOI: 10.1016/j.energy.2017.01.101].
[24] A. Shekhar, V. Prasanth, P. Bauer, M. Bolech, Economic Viability Study of an On-Road Wireless Charging System with a Generic Driving Range Estimation Method, Energies 9 (2016) 76. [DOI: 10.3390/en9020076].
[25] Land Transport Authority, Certificate of Entitlement Quota for November 2017 to January 2018 and Vehicle Growth Rate from February 2018, https://www.lta.gov.sg/apps/news/page.aspx?c=2&id=b010406e-6edf-4224-9cd1-928706cd6fe7, 2017. (accessed 2017-12-04).
[26] Land Transport Authority, Land Transport Master Plan 2013, https://www.lta.gov.sg/content/dam/ltaweb/corp/PublicationsResearch/files/ReportNewsletter/LTMP2013Report.pdf, 2013. (accessed 2017-09-11).
[27] Land Transport Guru, Go-Ahead Singapore BYD Electric Bus Trial, http://landtransportguru.net/go-ahead-singapore-byd-electric-bus-trial/, 2017. (accessed 2017-10-16).
[28] Land Transport Authority, Factsheet: Leveraging Technology for a Smarter and Greener Transport System, https://www.lta.gov.sg/apps/news/page.aspx?c=2&id=e09102cd-acd5-469e-8234-777b68e4e18a, 2017. (accessed 2017-10-16).
[29] Land Transport Guru, Electric Buses to be procured by LTA, http://landtransportguru.net/electric-buses-to-be-procured-by-lta/, 2017. (accessed 2018-06-25).
[30] NASA JPL, NASA Shuttle Radar Topography Mission Global 1 arc second, 2013.
[31] Energy Market Authority (EMA), Singapore Energy Statistics 2017, https://www.ema.gov.sg/cmsmedia/Publications_and_Statistics/Publications/SES17/Publication_Singapore_Energy_Statistics_2017.pdf, 2017. (accessed 2017-08-03).
[32] B. Ang, T. Fwa, A study on the fuel-consumption characteristics of public buses, Energy 14 (1989) 797–803. [DOI: 10.1016/0360-5442(89)90033-9].
[33] N.-O. Nylund, K. Erkkilä, T. Hartikka, Fuel Consumption and Exhaust Emissions of Urban Buses, Research Notes 2373, VTT, Espoo, Finland, 2007.
[34] S. Zhang, Y. Wu, H. Liu, R. Huang, L. Yang, Z. Li, L. Fu, J. Hao, Real-world fuel consumption and CO2 emissions of urban public buses in Beijing, Applied Energy 113 (2014) 1645–1655. [DOI: 10.1016/j.apenergy.2013.09.017].
[35] A. Lajunen, Energy consumption and cost-benefit analysis of hybrid and electric city buses, Transportation Research Part C: Emerging Technologies 38 (2014) 1–15. [DOI: 10.1016/j.trc.2013.10.008].
[36] A. Lajunen, Energy-optimal velocity profiles for electric city buses, in: 2013 IEEE International Conference on Automation Science and Engineering (CASE), IEEE, 2013, pp. 886–891. [DOI: 10.1109/CoASE.2013.6653956].
[37] A. Kunith, R. Mendelevitch, A. Kuschmierz, D. Goehlich, Optimization of fast charging infrastructure for electric bus transportation – Electrification of a city bus network, in: EVS29 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium, Montreal.
[38] K. Holmberg, P. Andersson, N.-O. Nylund, K. Mäkelä, A. Erdemir, Global energy consumption due to friction in trucks and buses, Tribology International 78 (2014) 94–114. [DOI: 10.1016/j.triboint.2014.05.004].
[39] National Research Council, Review of the 21st Century Truck Partnership, Second Report, National Academies Press, Washington, D.C., 2012.
[40] D. Perrotta, B. Ribeiro, R. J. Rossetti, J. L. Afonso, On the potential of regenerative braking of electric buses as a function of their itinerary, Procedia-Social and Behavioral Sciences 54 (2012) 1156–1167. [DOI: 10.1016/j.sbspro.2012.09.830].