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ORIGINAL RESEARCH

A multi-factor electric-bus (E-bus) energy consumption (EC) methodology for urban public transit routes

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Abstract
Advantages of electric buses (E-bus) in emission and air pollution reduction motivate local governments to replace conventionally fuelled public transit buses; however, the main drawbacks of the E-buses are range and charging duration. Estimation of daily energy consumption (EC) of E-buses is critical, which depends on various factors. This study proposes a multi-factor EC methodology considering public transit bus routes and operational characteristics (i.e., grade, journey speed, passenger load, etc.). After the analyses of complex bi-factor interactions among the selected parameters, the results lead to the development of a multi-factor E-bus EC estimation matrix, which is later used as a guide for EC estimation of PT E-bus routes. To better represent the EC of auxiliary system, the ambient temperature is also included as a factor. The methodology is tested along the two E-bus routes in Ankara, Türkiye. A total of 7 round-trip field data collection also included the observed state-of-charge (SOC) values at every bus stop, which was later used as a control value for the estimated E-bus route EC values; the slight difference between the estimated and observed SOC is assumed to stem from integer values of displayed SOC values. Analysis of auxiliary energy separately provides a more accurate evaluation of E-bus EC within a day, where night-time and daytime temperatures may vary significantly, as well as for different seasons (winter versus summer). The effect of passenger number, which can change dramatically during the peak and off-peak periods, can also be captured, as well.

Keywords Public transit · E-bus · Energy consumption · State-of-charge · E-bus operation

1 Introduction

The sustainable development goals of the United Nations include affordable and clean energy, sustainable cities and communities, and reasonable consumption and production. Cities are responsible for the consumption of 70% of the world's energy resources (Bibri & Krogstie, 2017), including the energy used for urban mobility. However, energy consumption (EC)

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mostly results in Greenhouse Gas (GHG) emissions, which leads to a climate change risk. This, in return, triggered a re-evaluation of energy use in the world. Current European Commission goals include the reduction of GHGs by 80–95% below 1990 levels by 2050. As the transport sector generates a quarter of the global CO_2 (Ku et al., 2021), there is an ongoing effort to transition away from petroleum-based fuels and establish a net-zero-emission system for the transport industry. For the transport sector, the European Commission aims for a reduction of at least 60% of GHG by 2050 from the transport sector with respect to 1990 levels (European Commission, 2011), which is higher than some other sectors. The use of alternative fuels and improving electric vehicle (EV) technology is one mitigation area for transportation emissions. Another mitigation option is to create a model shift from private cars to public transit (PT). Combining the two options brings the consideration of electric bus (E-bus) use in PT services into the policy development.

E-buses are introduced as a zero-emission alternative to replace conventionally fuelled buses. The undeniable advantage of E-buses has promoted cities to replace conventionally fuelled buses with electric ones, especially for public transit purposes, to achieve emission and air pollution reduction. In terms of air quality, tailpipe emissions are considered as the main source of harmful pollutants such as nitrous oxide (NO_x) and particulate matter (PM). Apart from CO_2 emission reduction, the results of studies in Stockholm suggested that bus electrification also mitigates local air pollution components, including NO_x and PM (Xylia et al., 2019). Figure 1 shows the e-bus stock of countries in 2023 (IEA, 2024), which shows the great stock development in China and India (two highly populated developing countries) as well as the USA, South Korea, and the UK. Many countries/states have been applying regulations to ensure the shift towards zero-emission buses which include battery, fuel cell and overhead wire (trolley) E-buses (Table 1). Although the target years for 100% Zero-Emission Bus procurement and fleet transition show differences, it is clear that there is a strong motivation towards using mostly Zero-Emission buses globally by 2050.

One of the main drawbacks of the E-buses for PT use is the range and the charging duration (K. Behnia et al., 2024; Chau et al., 2024; Liu et al., 2021). The capacity and the range of E-buses have been reported by the manufacturers: Depending on the bus size,



Fig. 1 Global e-bus stock according to IEA 2023 statistics

Table 1 100% zero-emission bus procurement and fleet targets (Wappelhorst & Rodriguez, 2021)

Country	Bus Procurement Target	Bus Fleet Target	Source (publication year)
AUT	2032	Not specified	Mobility Master Plan (2021)
Cape Verde	2035	2050	Electric Mobility Policy Charter (2019)
CHL	2035	Not specified	National Electromobility Strategy (2021)
COL	2035	Not specified	National law on electromobility (2019)
DNK	2025	2030	Climate and Air Plan (2018)
NZL	2025	2035	Government announcement (2021)
NLD	2025	2030	Mission Zero (2019)
USA-CA	2029	2040	Innovative Clean Transit (ICT) regulation (2018)
USA (16 states)	2050	Not specified	Memorandum of Understanding (2020)
CRI	Not specified	2050	Decarbonization Plan (2019)
AUT, CAN, CHL, DNK, FIN, LUX, NLD, NZL, NOR, CHE, TUR, GBR, URY	2040	Not specified	Memorandum of Understanding (2021)

the range of E-buses vary between 150 to 450 km for battery capacities of 180 kWh to 500 kWh, respectively (Gao et al., 2017; UITP, 2017). However, these published values are approximated from simulations based on testing results and vary with route conditions, weather, vehicle configuration, etc. Optimal conditions for E-bus range estimations assume temperate weather conditions, fewer stops (and express routes), optimal driver behaviour, minimal Heating, Ventilation and Air-conditioning (HVAC) usage and flatter terrain, any deviation from them causes inefficient to use battery power and lead to higher E-bus EC, and rapid reduction of range (Pinellas Suncoast Transit Authority, 2021). Thus, deployment of the E-bus fleets in a city must regard these aforementioned factors and PT route characteristics in detail.

1.1 Scope of the study

The main focus of this work lies in the development of a multi-factor total EC estimation methodology for E-bus routes that can be realistically calculated considering route and operational characteristics. Unlike other studies that focus solely on singular factors such as speed or passenger load (Fiori et al., 2019; Perugu et al., 2023; Yang & Liu, 2022), our approach integrates speed, grade, passenger load, and inter-stop distance. Complex interactions among these factors prevent the use of simple factor-based coefficients and simple interpolations, as can be seen in bi-factor analyses. Further analysis is used to develop a multi-factor EC estimation matrix, which is later used as a guide for the more realistic estimation of E-bus

route EC for PT services. This matrix provides the value of the mechanical EC per km for different scenarios based on different levels of i) journey speed, ii) grade, iii) passenger load, and iv) stop distance. Furthermore, the auxiliary energy (E_{aux}) requirements based on ambient temperature variations are incorporated in the estimation of the total EC, which are rarely addressed in existing studies. The E_{aux} component is calculated based on the ambient temperature of the E-bus service time, which may change during daytime versus night-time services, as well as summer versus winter conditions. Total EC estimation is used to determine the state-of-change (SOC) of the E-bus battery.

The proposed methodology is tested along the two E-bus routes in Ankara, Türkiye. A total of 7 round-trip field data collection, which included observed SOC values at every bus stop, provided the evaluation of the estimated E-bus Route EC and methodology. Analysis of E_{aux} separately provides a more accurate evaluation of E-bus use within a day, where night-time and daytime temperatures may vary significantly, as well as for different seasons (winter versus summer). The effect of passenger load, which can change dramatically during the peak and off-peak periods, can also be captured, as well.

The proposed E-bus route EC estimation method can be used to support the planning of deployment of E-buses in PT use by municipalities and planning agencies. It does not require extensive bus GPS track data, yet it can provide realistic results in terms of EC (or SOC) by considering multiple factors simultaneously, as well as their non-linear complex interactions; furthermore, the regenerative braking phenomenon is included to improve the realistic estimation capability of the method. The simplicity of the method is provided by the created EC estimation matrix, which can be used with basic PT route and travel characteristics data. The visual support of the matrix for the EC levels estimation makes it easily understood and used by non-engineering people (such as planners, PT analysts, decision-makers, etc.), who do not necessarily solve mechanical energy equations with advanced calculus requirements.

2 Factors affecting E-bus energy consumption (EC)

The battery technologies and the bus operation planning studies focus on maximizing the performance of the buses and optimizing the bus network system. The range of the E-buses is mainly dependent on battery size. However, although higher battery capacity provides more power, it also creates a significant extra load on the bus, which also increases energy consumption. Therefore, in terms of battery technology, the increase in range depends on the improvement of the power systems. On the other hand, in terms of bus operation planning, the adequacy of charging stations and the electricity grid system, as well as the number of buses operating and the fleet scheduling, depend on the performance of the e-buses. According to Gallet et al. (2018a) when the bus fleet is fully electrified, the heterogeneity of the driving profiles creates a burden on the electricity grid, causing high variance in energy requirements between different lines and at different times of day. Therefore, an energy consumption estimation is crucial for planning and deployment purposes.

2.1 Longitudinal dynamic model (LDM)

To estimate the EC of an E-bus, the longitudinal dynamic model (LDM) is frequently used in the literature (Liu et al., 2020; Wu et al., 2015; Asamer et al., 2016; Gao et al., 2017; Chen et al., 2021). The EC of E-buses is calculated based on the vehicle dynamics equation considering vehicle speed, total mass, route grade and acceleration, and the auxiliary sources of EC

consumption such as HVAC, lightening, door mechanism, etc. (Hjelkrem et al., 2021; Saadon Al-Ogaili et al., 2020). The mechanical energy calculations are affected by acceleration and deceleration profiles.

$$TotalEC = E_{LDM} + E_{aux}$$

$$E_{LDM} = \frac{\eta}{3600}\left[(MgC_r cos\varphi) + (Mgsin\varphi) + \left(\frac{1}{2}\rho AC_d v^2\right) + (Ma)\right]d$$

$$E_{aux} = E_{HVAC} + E_{other}$$

E_{LDM}: the mechanical energy required at the wheels to drive a distance d in kWh.

E_{aux}: the auxiliary energy required for heating, ventilation, lighting, etc., to drive a distance d in kWh.

η: the accumulated efficiency factor of E-bus.

M: the total mass of the vehicle, including the passenger loads and the vehicle weight.

φ: route grade.

C_r: coefficient of rolling resistance (0.006–0.02).

ρ: density of air (1.2 kg/m^3).

C_d: drag coefficient (0.6–0.8).

υ: speed (m/s).

a: acceleration (m/s^2).

d: distance (m).

The main problem when determining the EC is the auxiliary energy required for the system. The auxiliary energy accounts for door opening, lighting, heating, ventilation, etc. While ventilation and lighting are mostly dependent on travel time, the heating is also dependent on the difference between bus temperature and ambient temperature.

2.2 Speed and acceleration effect on the ELDM estimation

The relationship between speed and E_{LDM} in Fig. 2 shows that an optimum speed for E-bus travel lies between 25 and 35 km/h. In this study, the characteristics applied by Lajunen (2014) are implemented for the driving profile that ranges between 1.4 and 2.2 m/s^2. It is seen that only a slight change is observed as the optimal speeds.

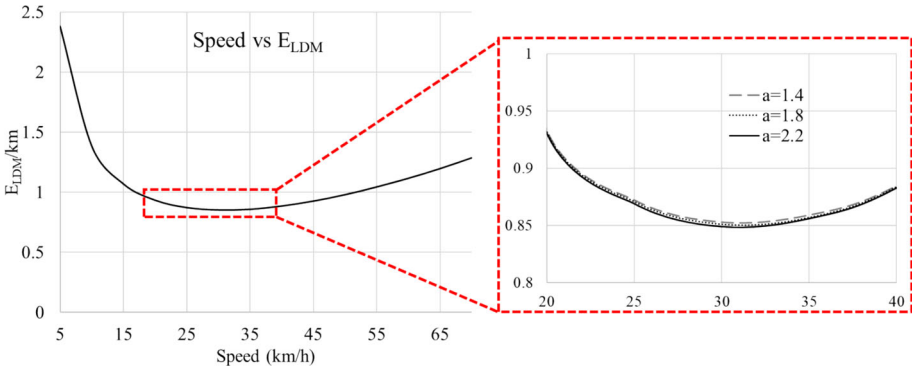


Fig. 2 Mechanical EC change by speed based on acceleration-deceleration rates stated by Lajunen (2014)

2.3 Regenerative braking

Regenerative braking is the process in which the vehicle regains some of the lost energy from deceleration back into the system. The regenerative braking occurs when the tractive force (F_{LDM}) is negative. This occurs when the vehicle is braking. Under these circumstances, the electric vehicles are able to convert this energy and store it back in the battery. The efficiency of the regenerative braking is important when calculating the EC of the vehicles. Gallet et al. (2018a), defined a regeneration factor that determines how much of the kinetic energy can be regenerated, and this factor is applicable only when the tractive force is negative. Hjelkrem et al. (2021) proposed that when calculating the EC, if P_{LDM} has a negative value and the speed is below 15 km/h, the mechanical energy (E_{LDM}) consumption is equal to zero. The authors suggest that for the regenerative braking to occur, a minimum speed should be gained, and that value of speed is 1 km/h. The regenerative braking is considered, but the efficiency of the energy gain is not stated in their study.

2.4 Auxiliary energy requirement

The EC related to auxiliary loads is highly dependent on the temperature since it is mostly governed by heating and ventilation. Hjelkrem et al. (Hjelkrem et al., 2021) estimated the EC based on LDM. The formulation of the auxiliary load on the battery was calculated by summing the heating, ventilation, and other loads. The energy required for heating was estimated considering the number of doors, flow rates of air exchange, and the ambient temperature. Comparing the estimated values with the actual EC values for 3266 trips, they concluded that the total EC of a trip can be estimated using the following formula:

$$Total\ EC = 1.33 \sum_{i=0}^{n} \frac{P_{ldm,i}}{\eta_{ebus}} \Delta t$$

where an additional 33% energy is assumed for E_{aux}. Similarly, Bartlomiejczyk et al. concluded that the E_{aux} requirement is responsible for almost half of the total EC, and in extreme cases (cold winter and hot summer), this value reaches up to 70%. On the other hand, there are also some studies that take the auxiliary energy into account as constant values. Gallet et al. (Gallet et al., 2018a) estimated the required power for auxiliary loads as 10kW for single-deck and 15 kW for double-deck buses. Vepsalainen et al. (2019) assumed that the auxiliary power ranges between 2 and 7 kW. Lajunen (2018) estimated the auxiliary power based on ambient temperature for mild, cold, or hot and extreme conditions as 6 kW, 14 kW, and 22 kW, respectively.

2.5 Effect of ambient temperature

In order to specifically identify the energy requirements for the auxiliary loads, many studies have been conducted to investigate the effect of climate conditions on the range of E-buses, but few provide analytical estimations on energy consumption related to HVAC systems, and most of them imply rather complex models. The previous research on energy consumption mostly focused on electric vehicles (EVs). However, these models are not applicable to an urban E-bus since the E-bus operates at a rather lower speed, with frequent stops and with a larger weight. Lajunen and Tammi (2019) estimated the relationship between auxiliary energy consumption and the ambient temperature. They presented a U-shaped curve with

Table 2 The range of nominal power of the main auxiliary systems in 12 m electric bus or trolleybus (Bartłomiejczyk & Kołacz, 2020)

System	Nominal power
Lightning	1–2 kW
Passenger information systems, ticket vending machine	1–3 kW
Charging of 24 V board batteries	0.5–2 kW
Air compressor	3–6 kW
Hydraulic pump	2–4 kW
Air condition	10–16 kW
Heating	5–25 kW

increasing power consumption with both increasing and decreasing temperatures. Li et al. (2021) analysed real-world data from 1024 E-buses between the ambient temperatures of 9–33° C and concluded that the overall energy consumption remains unchanged between 11 and 17° C and has a median value of 1.1 kWh/km. A similar shape is obtained by Todorut et al. (2020) with 1.125 kWh/km at an optimal ambient temperature of 21.2° C. For most of the studies, the effect of the ambient temperature is evaluated compared to the total energy consumption. Ji et al. (2022) concluded that the optimum operation temperature is 23.7° C, and the energy consumption increases by 47% and 9% at − 27° C and 35° C, respectively. Most of the change in auxiliary energy requirement based on ambient temperature is attributed to the AC system.

Although AC covers most of the auxiliary loads, services such as lighting, passenger information systems, air compressors, and the hydraulic pump also require energy. Bartłomiejczyk and Kołacz (2020) reported the auxiliary power requirements for a 12 m electric bus (Table 2). Lajunen et al. (2019) reported that the constant power consumption without the AC is reported as 5kW. Basma et al. (2020) evaluated the auxiliary energy requirement based on vehicle motion and the ambient temperature. Basma et al. (2020) introduced an average HVAC energy demand estimation equation. The auxiliary loads are calculated with respect to the ambient temperature (T) over travel time (t).

$$E_{aux} = \frac{t}{3600}\left[-0.0001T^3 + 0.033T^3 - 1.0793T^2 + 10.648\right]$$

2.6 Energy consumption (EC) models

There are two common analyses used in the literature to study the association between the parameters and e-bus energy consumption: sensitivity analysis and regression analysis. Sensitivity analysis describes the importance of each input parameter in determining the variability of the model response, whereas the regression models determine the significance or the lack of the independent input parameters on the energy consumption (Abdelaty & Mohamed, 2021). Various models are formed based on different parameters, and these models are mainly derived based on real-life data. Liu et al. (2020) proposed a multi-objective index system to evaluate the operating performance of the electric buses. The factors are classified into three categories: i) operational, ii) topological, and iii) external.

It can be seen that the most frequently used factors are speed and acceleration, followed by number of stops, grade, and passenger load. Teoh et al. (2018) used a linear regression model

to estimate the impact of route length and passenger loading on e-bus EC. The route length and passenger loading are found as the significant operational parameters; however, it is also argued that the operational parameters are greatly affected by various external parameters, including the headway and the charging type. Vepsäläinen (2019) conducted a sensitivity analysis based on the results of multiple linear regression analysis to interpret the variation in the EC rates due to the operation and environmental parameters. A linear regression analysis was used to determine the correlated and uncorrelated operation parameters and the parameters affecting the EC, also concluding the significance of the driver's aggressiveness and the stops per km. Galvin (2017) developed a multivariate linear regression model to study the impact of driving behaviour parameters, such as acceleration/deceleration rates and average speed on EV EC, while ordinary least squares regression and multilevel mixed-effects regression models were used to assess the impact of the external parameters, such as temperature and HVAC. Furthermore, several multiple linear regression models were developed to predict the EC based on vehicular parameters (i.e. rolling resistance and drag coefficient), topological parameters (i.e. road grade and route length), operational parameters (i.e. average speed and acceleration/deceleration rates), and external parameters including temperature, auxiliary power, and HVAC (Liu et al., 2017; De Cauwer et al., 2017; Gao et al., 2018; De Cauwer et al., 2015; Kunith et al., 2017; Neaimeh et al., 2013). Ma et al. (2021) estimated the effect of route and driving profiles for E-buses and conventional diesel buses. The factors investigated included average journey speed, route grade, number of stops, average stop distance, average stop-level dwell time, route directness, and time of day. It is concluded that the parameters have non-linear effects on the EC and that the route characteristics (number of stops and stop spacing) have a larger impact on e-bus EC.

3 Methodology

3.1 Estimation of E-bus energy consumption (EC) for public transit bus routes

The framework to construct an E-bus route EC profile based on major route and operational factors affecting E-bus performance is shown in Fig. 3. The studied factors are listed as follows;

- *Speed and Acceleration:* The average speed calculated in between stops (km/h) and assumed constant acceleration (m/s^2)
- *Road Grade:* The average road grade calculated between stop points (%)
- *Passenger Load:* The number of passengers in the E-bus
- *Stop distance*: distance between stop points (m)

In the first step, for each route segment between stops, speed profile, acceleration, total mass (based on passenger number and bus mass), and road gradient are determined to calculate the mechanical EC (E_{LDM}). To do so, a speed profile is constructed assuming a constant inter-stop speed value and constant acceleration/deceleration value before and after stop dwellings. A bi-factor analysis of the selected factors is conducted to analyse the effect of each parameter in combination with another. This provided the relationship between factors and how they affect the E_{LDM} characteristics. By combining the effect of the selected factors and the ambient temperature, the change in mechanical EC is analysed in combination, enabling the creation of a mechanical EC estimation matrix which provides a unit EC/km value in kWh that accounts for the energy required for motion. The effect of ambient temperature is added separately as kWh/km as suggested by Basma et al. (2020). Finally, to estimate EC along a

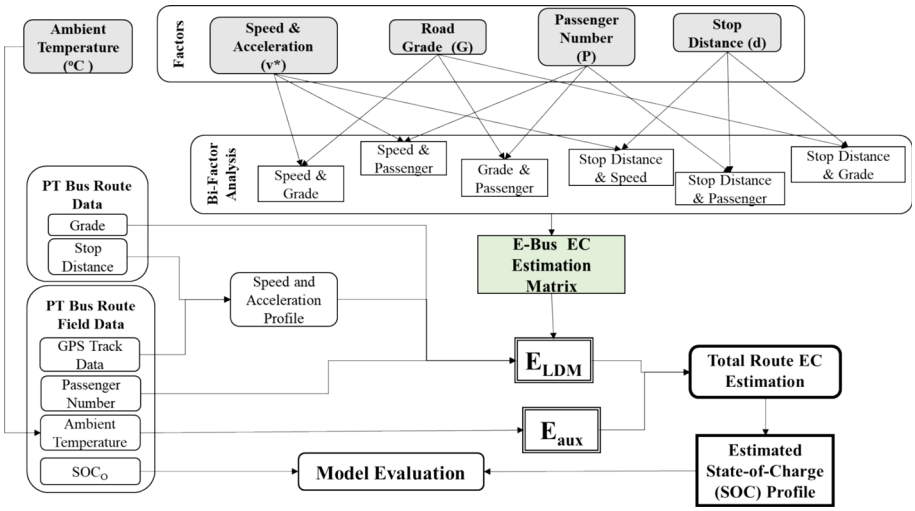


Fig. 3 E-bus EC estimation framework for public transit bus routes

route for an E-bus operated for PT services, a piecewise linear cumulative energy usage is accepted for a given route, which can be simply calculated as the sum of estimated EC in segments between stop points.

It should be noted here that the proposed methodology excludes factors related to vehicle design characteristics (such as frontal area, battery efficiency, and drag coefficient) and road conditions (such as coefficient of rolling resistance), which are more important for fleet management and road asset management decisions.

3.2 Factors for E-bus EC estimation

The assumed values for the matrix generation are summarized in Table 3. As urban PT services are not expected to operate at speeds higher than 50 km/hr, the average speed values are assumed to change between 10 km/hr (congested traffic conditions) and 50 km/hr. A constant acceleration/deceleration value of 1.8 m/s^2 is assumed as the LDM formulation is not sensitive to it. All the parameters are inputted to the analysis as provided in the table, but these values can be altered for specific purposes. For road grades, a range of [− 5%, 5%] is assumed, which covers level and rolling terrain conditions. The E-bus-related parameters, such as bus weight and frontal area, are inputted by assuming a 12 m standard E-bus.

3.3 Bi-factor analysis of E-bus EC factors

The bi-factor analysis is performed to analyse the effects of the factors affecting the mechanical EC of E-buses (see Fig. 4). The MATLAB Simulink Curve fitting is used to plot the effect of the factors in 3-dimensions, where the unchanged factors have assumed values of v = 30 km/h, G = 0%, P_0, d = 250 m, whenever necessary. As can be seen from the graphs, not every parameter affects the EC linearly. The relationship between the mechanical EC with respect to speed and grade is presented in Fig. 4a. The effect of grade is linear, and mechanical EC increases as grade increases. High speed on high grades creates higher EC

Table 3 Values of factors used in analysis

Factor	Parameter	Values	Notes
Speed & acceleration	Speed (v) in km/hr Acceleration (a)	[10; 50] km/hr 1.8 m/s^2	Commonly 1.8 m/s^2 acceleration assumed (if not applicable, gradually increased with 0.1 increments fitting the travel time and inter-stop distance)
Route grade	Road Grade	[− 5%; 5%]	Higher grades can be introduced if necessary
Passenger load*	Passenger Number	[0;100]	80 kg standard passenger mass P_0: empty (0 passengers) P_HS: half-seated (~ 17 passengers) P_AS: all-seated (~ 34 passengers) P_HF: half-full (~ 50 passengers) P_FL: full (~ 100 passengers)
Stop distance	Distance between PT stops	[100;1000]m	Longer distances can be introduced if necessary

*The total weight of the passenger load is summed with the bus weight to obtain the total mass for EC calculations

values, exceeding 4 kWh/km. Figure 4b shows that the effect of passenger load increases as the driving speed increases. Figure 4c shows that the passenger load has a significant effect with increasing road gradients, however, this effect decreases with negative grades and even negative for grades steeper than − 3%. This is mainly attributed to the regenerative braking concept that decreases the energy requirement when braking. The effect of the distance between stops is shown in Fig. 4d–f. The effect of stop distance does not show a significant difference with speed for stop distance values above 500 m (Fig. 4d). A similar trend is observed for the stop distance relationship between grade and passenger load (Fig. 4e–f). When buses operate at full capacity, the EC is the highest for each stop distance, however, the effect of passenger load is most significantly observed for the case of 100 m stop distance.

The bi-factor analysis showed that high passenger load, high grade, and low stop distance have a significant effect on the required energy consumption. Especially when the stop distance and speed are investigated with other parameters, a non-linear trend is observed. This shows that the parameters should be analysed in combination, and the mechanical EC should be either calculated through the equations for each segment, or a combined matrix analysis should be performed considering each factor.

3.4 Multi-factor analysis of E-bus total EC

As an extension of bi-factor analysis, the mechanical EC variability based on all four factors can be summarized in a matrix, which can be later adjusted to include the energy consumption for the auxiliary systems, to be used in the estimation of total EC along a given PT route as described below.

The impact of all four factors on the mechanical EC can be simplified as shown in Table 4, where the continuous values of the factors are exchanged with selected intermediate values, such as for 11 values of grades between − 5% to 5%, and 5 stop distances values {100 m, 250 m, 500 m, 750 m, 1000 m}. Also, 5 different speed values {10 km/hr, 20 km/hr, 30 km/hr,

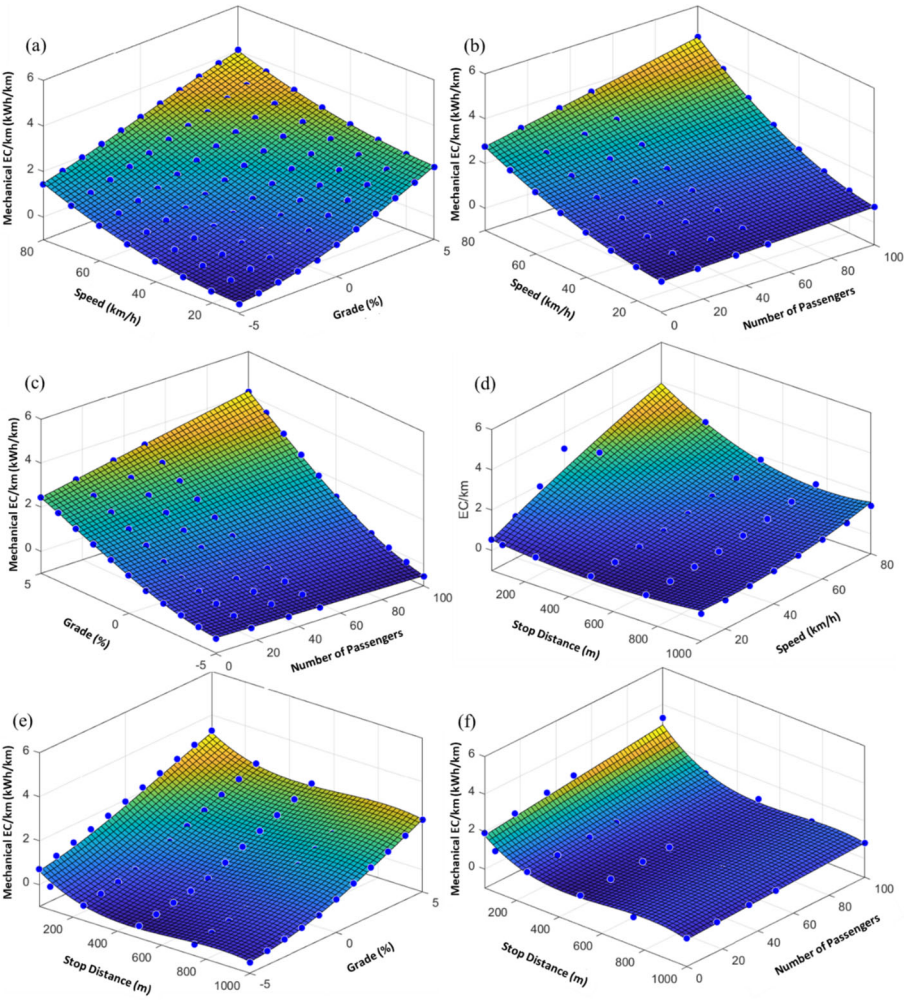


Fig. 4 Bi-factor analysis of mechanical EC based on **a** speed & grade, **b** speed & passenger load, **c** grade & passenger load, **d** speed & stop distance, **e** grade & stop distance, **f** passenger load & stop distance

40 km/hr, 50 km/hr} and 4 different passenger load levels {17 people, 35 people, 500 people and 100 people} are assumed in addition to an empty bus situation. It is important to note that these values represent EC per km and are constructed for a standard 12 m E-bus with 11-ton vehicle weight and 80 kg passenger load without considering the auxiliary loads.

For any route segment between two bus stops and operational characteristics, the mechanical EC can be easily interpolated from the boundary values from the matrix above. For example,

- For an empty E-bus traveling between two bus stops with a distance of 500 m apart, which will be traveled at a speed of 20 km/hr at an upgrade of 3%, the ELDM will be 1.52 kWh/km
- If the bus has 25 people on board, this value would rise to 1.79 kWh/km,

Table 4 Effects of farming system and planting time on the quality of broad bean seeds

Road Gradient (%)	Stop Distance (m)	Speed (km/h)	10					20					30					40					50				
		Number of Passengers	0	17	35	50	100	0	17	35	50	100	0	17	35	50	100	0	17	35	50	100	0	17	35	50	100
-5	1000		-0.59	-0.67	-0.74	-0.81	-1.03	-0.56	-0.63	-0.71	-0.77	-0.98	-0.50	-0.57	-0.64	-0.70	-0.90	-0.43	-0.49	-0.55	-0.61	-0.78	-0.33	-0.38	-0.44	-0.49	-0.64
	750		-0.59	-0.66	-0.74	-0.81	-1.02	-0.55	-0.62	-0.69	-0.76	-0.96	-0.48	-0.55	-0.62	-0.67	-0.86	-0.39	-0.45	-0.51	-0.55	-0.72	-0.27	-0.32	-0.36	-0.40	-0.54
	500		-0.59	-0.66	-0.74	-0.80	-1.01	-0.53	-0.60	-0.67	-0.73	-0.93	-0.44	-0.50	-0.56	-0.61	-0.79	-0.32	-0.36	-0.41	-0.45	-0.59	-0.15	-0.18	-0.22	-0.24	-0.33
	250		-0.57	-0.64	-0.72	-0.78	-0.99	-0.47	-0.53	-0.60	-0.65	-0.83	-0.31	-0.36	-0.40	-0.44	-0.57	-0.09	-0.11	-0.13	-0.14	-0.19	0.20	0.22	0.23	0.24	0.28
	100		-0.53	-0.60	-0.67	-0.73	-0.92	-0.30	-0.34	-0.39	-0.42	-0.54	0.07	0.07	0.08	0.08	0.10	0.59	0.66	0.73	0.79	0.99	1.25	1.39	1.55	1.67	2.10
-4	1000		-0.44	-0.50	-0.55	-0.60	-0.76	-0.41	-0.46	-0.51	-0.56	-0.71	-0.35	-0.40	-0.45	-0.49	-0.63	-0.27	-0.31	-0.36	-0.39	-0.51	-0.17	-0.20	-0.24	-0.26	-0.36
	750		-0.44	-0.49	-0.55	-0.60	-0.76	-0.40	-0.45	-0.50	-0.55	-0.70	-0.33	-0.37	-0.42	-0.46	-0.59	-0.23	-0.27	-0.30	-0.34	-0.44	-0.11	-0.13	-0.16	-0.18	-0.25
	500		-0.43	-0.49	-0.55	-0.59	-0.75	-0.38	-0.43	-0.48	-0.52	-0.66	-0.28	-0.32	-0.36	-0.40	-0.51	-0.15	-0.18	-0.20	-0.23	-0.30	0.02	0.01	0.00	-0.01	-0.03
	250		-0.42	-0.47	-0.53	-0.57	-0.73	-0.32	-0.36	-0.40	-0.44	-0.56	-0.15	-0.17	-0.19	-0.21	-0.28	0.09	0.10	0.10	0.10	0.12	0.40	0.43	0.47	0.51	0.62
	100		-0.38	-0.42	-0.47	-0.52	-0.65	-0.14	-0.15	-0.17	-0.19	-0.24	0.26	0.29	0.32	0.34	0.43	0.82	0.91	1.01	1.09	1.37	1.51	1.69	1.87	2.03	2.55
-3	1000		-0.29	-0.33	-0.36	-0.40	-0.50	-0.25	-0.29	-0.32	-0.35	-0.45	-0.20	-0.22	-0.25	-0.28	-0.36	-0.11	-0.13	-0.16	-0.18	-0.24	-0.01	-0.02	-0.03	-0.04	-0.08
	750		-0.29	-0.32	-0.36	-0.39	-0.50	-0.24	-0.28	-0.31	-0.34	-0.43	-0.17	-0.20	-0.22	-0.25	-0.32	-0.07	-0.09	-0.10	-0.12	-0.17	0.06	0.05	0.05	0.05	0.03
	500		-0.28	-0.32	-0.36	-0.39	-0.49	-0.22	-0.25	-0.28	-0.31	-0.40	-0.12	-0.14	-0.16	-0.18	-0.24	0.01	0.01	0.00	0.00	-0.02	0.19	0.20	0.22	0.23	0.27
	250		-0.27	-0.30	-0.34	-0.37	-0.46	-0.16	-0.18	-0.20	-0.22	-0.28	0.02	0.02	0.02	0.02	0.01	0.27	0.30	0.32	0.35	0.43	0.59	0.65	0.72	0.77	0.96
	100		-0.22	-0.25	-0.28	-0.30	-0.38	0.03	0.04	0.04	0.04	0.05	0.45	0.50	0.56	0.61	0.76	1.04	1.16	1.29	1.40	1.75	1.77	1.98	2.20	2.38	3.00
-2	1000		-0.14	-0.16	-0.17	-0.19	-0.24	-0.10	-0.12	-0.13	-0.14	-0.19	-0.04	-0.05	-0.06	-0.07	-0.09	0.04	0.04	0.04	0.04	0.03	0.15	0.16	0.17	0.18	0.20
	750		-0.14	-0.15	-0.17	-0.19	-0.24	-0.09	-0.10	-0.12	-0.13	-0.17	-0.02	-0.02	-0.03	-0.03	-0.05	0.09	0.09	0.10	0.10	0.11	0.22	0.24	0.26	0.27	0.32
	500		-0.13	-0.15	-0.16	-0.18	-0.23	-0.07	-0.08	-0.09	-0.10	-0.13	0.04	0.04	0.04	0.04	0.04	0.18	0.19	0.21	0.22	0.27	0.36	0.40	0.43	0.46	0.56
	250		-0.11	-0.13	-0.14	-0.16	-0.20	0.00	0.00	0.00	-0.01	-0.01	0.19	0.21	0.23	0.24	0.30	0.45	0.50	0.55	0.59	0.74	0.79	0.87	0.96	1.04	1.29
	100		-0.06	-0.07	-0.08	-0.09	-0.11	0.20	0.23	0.25	0.27	0.34	0.64	0.72	0.80	0.87	1.09	1.26	1.41	1.57	1.70	2.14	2.03	2.27	2.52	2.74	3.45
-1	1000		0.02	0.02	0.02	0.02	0.02	0.07	0.08	0.08	0.08	0.10	0.16	0.17	0.18	0.19	0.22	0.28	0.30	0.32	0.33	0.38	0.43	0.46	0.49	0.51	0.59
	750		0.02	0.02	0.02	0.03	0.03	0.08	0.09	0.09	0.10	0.12	0.18	0.20	0.21	0.22	0.26	0.32	0.35	0.37	0.39	0.46	0.50	0.54	0.58	0.61	0.72
	500		0.03	0.03	0.03	0.03	0.04	0.11	0.12	0.12	0.13	0.16	0.24	0.26	0.28	0.30	0.35	0.42	0.45	0.49	0.52	0.62	0.64	0.69	0.75	0.80	0.96
	250		0.04	0.05	0.05	0.06	0.07	0.18	0.19	0.21	0.23	0.28	0.39	0.43	0.48	0.51	0.63	0.69	0.76	0.83	0.90	1.11	1.05	1.17	1.28	1.38	1.71
	100		0.10	0.11	0.12	0.13	0.16	0.39	0.43	0.48	0.52	0.65	0.86	0.96	1.07	1.16	1.45	1.51	1.69	1.87	2.03	2.55	2.29	2.56	2.85	3.09	3.90
0	1000		0.37	0.42	0.47	0.51	0.64	0.43	0.47	0.53	0.57	0.71	0.51	0.57	0.62	0.67	0.83	0.63	0.69	0.75	0.81	0.99	0.78	0.85	0.92	0.98	1.19
	750		0.38	0.42	0.47	0.51	0.65	0.44	0.49	0.54	0.58	0.73	0.54	0.59	0.65	0.70	0.87	0.67	0.74	0.81	0.87	1.06	0.84	0.92	1.01	1.08	1.31
	500		0.38	0.43	0.48	0.52	0.66	0.46	0.51	0.57	0.61	0.77	0.59	0.65	0.72	0.77	0.96	0.76	0.84	0.92	0.99	1.22	0.97	1.07	1.17	1.26	1.54
	250		0.40	0.45	0.50	0.54	0.68	0.53	0.59	0.65	0.71	0.89	0.73	0.82	0.90	0.98	1.22	1.02	1.13	1.25	1.35	1.67	1.37	1.52	1.67	1.81	2.25
	100		0.45	0.50	0.56	0.61	0.77	0.73	0.81	0.91	0.98	1.23	1.18	1.32	1.47	1.59	2.00	1.79	2.01	2.23	2.42	3.04	2.55	2.85	3.18	3.45	4.35
1	1000		0.73	0.82	0.92	0.99	1.26	0.78	0.87	0.97	1.05	1.33	0.87	0.96	1.07	1.15	1.44	0.98	1.08	1.19	1.29	1.59	1.12	1.24	1.36	1.46	1.79
	750		0.73	0.82	0.92	1.00	1.26	0.79	0.89	0.99	1.07	1.34	0.89	0.99	1.09	1.18	1.48	1.02	1.13	1.25	1.34	1.66	1.19	1.31	1.44	1.54	1.90
	500		0.74	0.83	0.93	1.00	1.27	0.81	0.91	1.01	1.10	1.38	0.94	1.04	1.15	1.25	1.56	1.10	1.22	1.35	1.46	1.81	1.31	1.45	1.59	1.72	2.12
	250		0.75	0.85	0.94	1.03	1.30	0.88	0.98	1.09	1.18	1.49	1.08	1.20	1.33	1.44	1.81	1.35	1.50	1.66	1.79	2.24	1.68	1.87	2.07	2.23	2.79
	100		0.80	0.90	1.00	1.09	1.38	1.07	1.19	1.33	1.44	1.82	1.50	1.67	1.86	2.02	2.54	2.08	2.33	2.59	2.81	3.53	2.81	3.15	3.50	3.80	4.80
2	1000		1.09	1.22	1.36	1.48	1.87	1.14	1.27	1.42	1.54	1.94	1.22	1.36	1.51	1.63	2.05	1.33	1.48	1.63	1.76	2.20	1.47	1.63	1.79	1.93	2.39
	750		1.09	1.22	1.37	1.48	1.88	1.15	1.28	1.43	1.55	1.96	1.24	1.38	1.54	1.66	2.09	1.37	1.52	1.68	1.82	2.27	1.53	1.69	1.86	2.01	2.49
	500		1.10	1.23	1.37	1.49	1.89	1.17	1.31	1.46	1.58	1.99	1.28	1.43	1.59	1.72	2.16	1.44	1.61	1.78	1.92	2.40	1.64	1.82	2.01	2.17	2.70
	250		1.11	1.25	1.39	1.51	1.91	1.23	1.37	1.53	1.66	2.09	1.42	1.58	1.76	1.91	2.39	1.67	1.87	2.07	2.24	2.81	1.99	2.22	2.46	2.66	3.33
	100		1.15	1.29	1.44	1.57	1.98	1.41	1.58	1.76	1.91	2.40	1.81	2.03	2.26	2.45	3.09	2.36	2.65	2.95	3.20	4.03	3.07	3.44	3.83	4.16	5.25
3	1000		1.44	1.62	1.81	1.97	2.49	1.49	1.67	1.86	2.02	2.55	1.57	1.76	1.95	2.11	2.66	1.68	1.87	2.07	2.24	2.80	1.82	2.01	2.22	2.40	2.98
	750		1.45	1.62	1.81	1.97	2.49	1.50	1.68	1.88	2.04	2.57	1.59	1.78	1.98	2.14	2.69	1.72	1.91	2.12	2.29	2.87	1.87	2.08	2.29	2.48	3.08
	500		1.45	1.63	1.82	1.98	2.50	1.52	1.70	1.90	2.06	2.60	1.63	1.83	2.03	2.20	2.77	1.79	1.99	2.21	2.39	2.99	1.98	2.20	2.43	2.63	3.28
	250		1.46	1.64	1.84	1.99	2.52	1.58	1.77	1.97	2.14	2.70	1.76	1.97	2.19	2.37	2.98	2.00	2.24	2.48	2.69	3.37	2.31	2.57	2.85	3.09	3.87
	100		1.50	1.69	1.89	2.05	2.59	1.74	1.96	2.18	2.37	2.99	2.13	2.38	2.66	2.88	3.63	2.65	2.97	3.30	3.58	4.52	3.33	3.73	4.16	4.51	5.69
4	1000		1.80	2.02	2.26	2.45	3.10	1.85	2.07	2.31	2.51	3.17	1.92	2.15	2.39	2.59	3.27	2.03	2.26	2.51	2.72	3.41	2.16	2.40	2.66	2.87	3.58
	750		1.80	2.02	2.26	2.46	3.11	1.86	2.08	2.32	2.52	3.18	1.94	2.17	2.42	2.62	3.30	2.06	2.30	2.55	2.76	3.46	2.21	2.46	2.72	2.94	3.67
	500		1.81	2.03	2.27	2.46	3.12	1.87	2.10	2.34	2.54	3.21	1.98	2.22	2.47	2.67	3.37	2.13	2.38	2.64	2.86	3.58	2.31	2.58	2.85	3.08	3.86
	250		1.82	2.04	2.28	2.48	3.14	1.93	2.16	2.41	2.61	3.30	2.10	2.35	2.61	2.83	3.57	2.33	2.60	2.89	3.14	3.94	2.62	2.92	3.24	3.51	4.40
	100		1.86	2.09	2.33	2.53	3.20	2.08	2.34	2.60	2.83	3.57	2.44	2.74	3.05	3.31	4.18	2.93	3.29	3.66	3.97	5.01	3.59	4.02	4.48	4.87	6.14
5	1000		2.16	2.42	2.70	2.94	3.72	2.20	2.47	2.75	2.99	3.78	2.28	2.55	2.84	3.08	3.87	2.38	2.66	2.95	3.19	4.01	2.51	2.79	3.09	3.34	4.18
	750		2.16	2.42	2.71	2.94	3.72	2.21	2.48	2.76	3.00	3.79	2.29	2.57	2.86	3.10	3.91	2.41	2.69	2.99	3.24	4.06	2.55	2.84	3.15	3.41	4.26
	500		2.16	2.43	2.71	2.95	3.73	2.23	2.50	2.78	3.02	3.82	2.33	2.61	2.90	3.15	3.97	2.47	2.76	3.07	3.32	4.17	2.65	2.95	3.27	3.54	4.43
	250		2.17	2.44	2.73	2.96	3.75	2.27	2.55	2.84	3.09	3.90	2.44	2.73	3.04	3.30	4.16	2.66	2.97	3.31	3.58	4.51	2.93	3.27	3.63	3.94	4.94
	100		2.21	2.48	2.77	3.01	3.81	2.42	2.72	3.03	3.29	4.16	2.76	3.09	3.45	3.74	4.72	3.22	3.61	4.02	4.36	5.50	3.85	4.32	4.81	5.22	6.59

Finally, the total EC values should be calculated by summing the mechanical EC and the auxiliary power requirement based on ambient temperature and travel time. To illustrate the total EC variation, the auxiliary power requirement is kept constant as 10 kWh and added to the mechanical energy consumption based on the driving duration as suggested in the literature (Gallet et al., 2018b). It can be seen that the EC can be significantly affected by road and operation parameters and can reach up to almost 4 times the reported EC values in the literature. For example, if the given range for an E-bus is 360 km, considering that the actual EC could be up to 4 times the reported value, for this specific bus, it should be assumed that under extreme conditions, this range could be decreased to almost 90 km. Also,

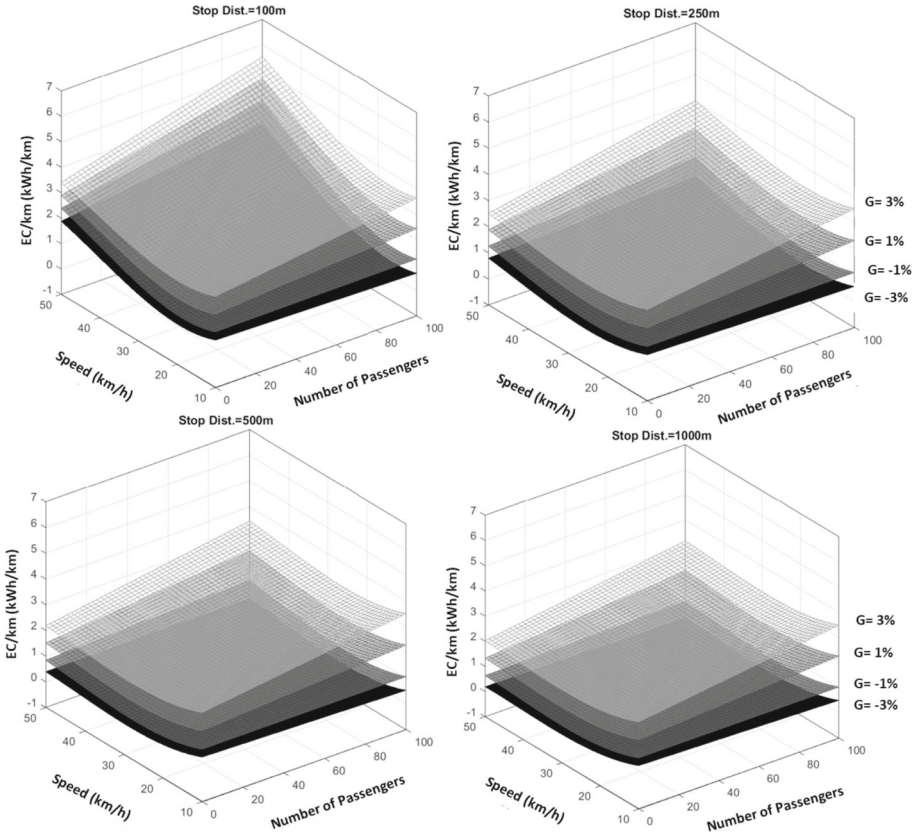


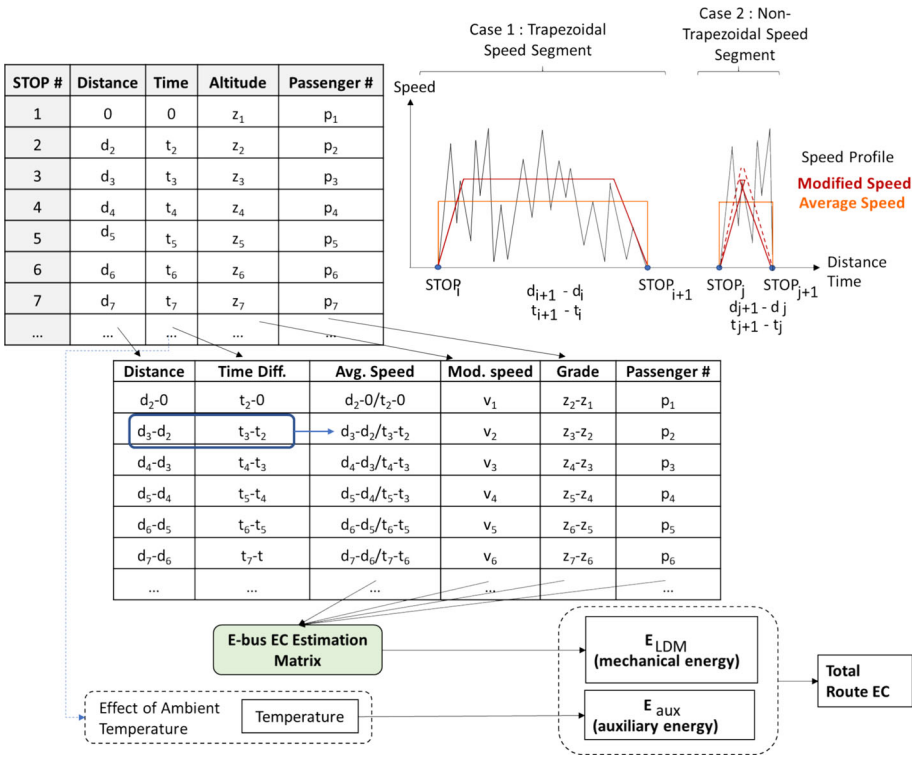
Fig. 5 Combined effects of passenger load, speed, road gradient, and stop distance on mechanical EC

the effect of the auxiliary loads is significantly high at low speeds due to the increase in the driving time.

The true nature of nonlinearity in the total EC can be visualized in the series of 3-dimensional graphs showing the variability of speed vs passenger load for selected grade and stop distance values (see Fig. 5), which also include E_{aux}. For 100 m stop distance, at 3% grade EC reaches to around 5.5 kWh/km, whereas when the stop distance is increased to 500 m the it can drop to around 3.5 kWh/km or even to negative values at negative grade and high stop distance at optimum speeds due to regenerative braking mechanism.

3.5 E-bus route total EC estimation using field data

To evaluate the performance of the proposed methodology, the total EC of E-bus routes is estimated by using field observations. For this purpose, E-bus routes are divided into road segments based on stop locations. The data required for the analysis include the distance between stops, time difference between stop locations, passenger load throughout the journey, and the altitude of each stop. For each route, the analysis is based on the stop locations, assuming that stopping only occurs at stop points (Fig. 6). The average speed between stops



STOP #	Distance	Time	Altitude	Passenger #
1	0	0	z_1	p_1
2	d_2	t_2	z_2	p_2
3	d_3	t_3	z_3	p_3
4	d_4	t_4	z_4	p_4
5	d_5	t_5	z_5	p_5
6	d_6	t_6	z_6	p_6
7	d_7	t_7	z_7	p_7
...	...	...	...	...

Distance	Time Diff.	Avg. Speed	Mod. speed	Grade	Passenger #
d_2-0	t_2-0	d_2-0/t_2-0	v_1	z_2-z_1	p_1
d_3-d_2	t_3-t_2	d_3-d_2/t_3-t_2	v_2	z_3-z_2	p_2
d_4-d_3	t_4-t_3	d_4-d_3/t_4-t_3	v_3	z_4-z_3	p_3
d_5-d_4	t_5-t_4	d_5-d_4/t_5-t_3	v_4	z_5-z_4	p_4
d_6-d_5	t_6-t_5	d_6-d_5/t_6-t_5	v_5	z_6-z_5	p_5
d_7-d_6	t_7-t	d_7-d_6/t_7-t_6	v_6	z_7-z_6	p_6
...	...	...	...	...	...

Fig. 6 E-bus total EC estimation methodology for a PT route

is calculated, and a constant speed profile is constructed between stops assuming the acceleration and deceleration value is equal to 1.8 m/s^2 so that a trapezoidal shape is reached for the speed profile (Case 1: Trapezoidal speed segment). For the cases where 1.8 m/s^2 acceleration and deceleration are not enough to construct a speed profile within the time and distance difference between stops, the acceleration and deceleration value is increased with a 0.1 increment (Case 2: non-trapezoidal speed).

The EC per km values are interpolated through the EC estimation matrix provided using the distance between stops, speed, number of passengers, and road gradient, and the energy required for the auxiliary services is calculated based on the ambient temperature and travel time. The required auxiliary energy requirement is estimated based on the equation provided by Basma et al. (Basma et al., 2020). The total driving time is considered for the estimation of the auxiliary energy requirement. This also covers the energy consumption during the dwell time. Finally, the sum of these energy values is combined to construct the estimated energy profile of the route. (Fig. 6).

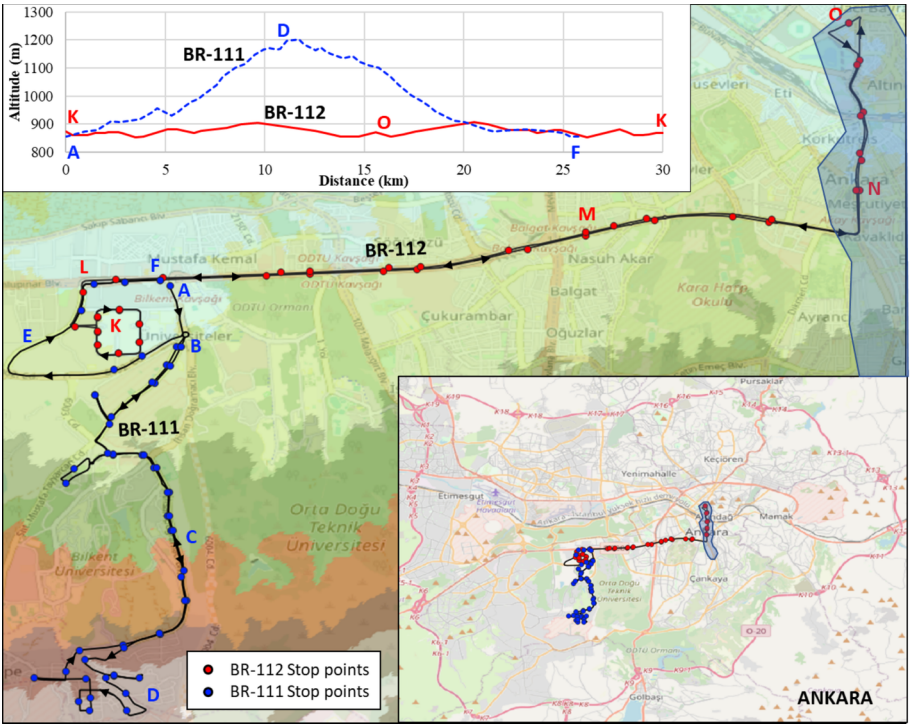


Fig. 7 Details on test routes BR-111 and BR-112

4 Case study: E-bus routes in Ankara

4.1 E-bus route characteristics

Two electric bus routes in Ankara are selected for the case study implementation. Bus Route 112 (BR-112) has a length of approximately 32 km and 47 stop points, and Bus Route 111 (BR-111) has a length of 27 km and 52 stop points (Fig. 7). BR-112 connects the CBD to an outbound destination through an urban arterial. This destination is a hospital shown with point K on the map. While points L and M lie on the urban arterial, points N and O are within the CBD. The journey for BR-112 starts at point K and ends at point O (BR-112 Inbound). However, since no charging activity is performed at point O, the route is studied as a loop (K–O–K) combining BR-112 Inbound and BR-112 Outbound services for better demonstration and comparison of results. BR-111 provides a service from the urban arterial to the rural regions of the city. Points A and F are within a PT hub that connects metro lines and bus lines. Point D is the highest elevation point that BR-111 reaches. The elevation profile of the selected routes is also shown in Fig. 7. As can be seen, BR-111 has a significantly high route gradient. This will contribute to the discussion on the effect of grade on the EC.

4.2 E-bus field data collection

The field data is gathered with an operating 12-m E-bus in Ankara (Fig. 8a). The buses are charged in the depot, and no intermediate charging is provided. The passenger capacity is 87



Fig. 8 12-m E-bus operating in Ankara along two selected PT Routes

passengers with 34 seats. The test is done for an E-bus with a 280 kWh battery capacity under normal operating conditions. Speed, altitude, and station km values are gathered through a mobile GPS Tracker. The time of arrival and departure from the stop is recorded to match with the GPS data, and the passenger number is counted throughout the journey to determine the occupancy. The obtained results and operation details for BR-112 Inbound, BR-112 Outbound, and BR-111 are summarized in Table 5.

Table 5 E-bus observed EC data summary

Route	Departure Time	Arrival Time	Journey Time (min	Amb. Temp (^{o}C)	SOC-Start (%)	SOC-End (%)
Aug 9 2023						
112-1-Inb	06:40	07:10	30	25	94	89
112-1-Outb	07:25	08:18	53	27	89	80
112-2-Inb	08:20	08:58	38	27	80	74
112-2-Outb	09:10	09:56	46	28	74	67
112-3-Inb	15:05	15:47	42	38	64	56
112-3Outb	16:10	16:43	33	36	55	48
112-4Inb	17:05	17:56	51	36	47	38
112-4Outb	18:30	19:04	34	35	36	29
Aug 10 2023						
111-1	15:05	15:58	53	37	65	50
111-2	16:25	17:15	50	36	50	35
111-3	18:10	19:00	50	33	56	26

The state of charge (SOC) is gathered through the values shown on the console (Fig. 8b) at each stop. The energy consumption is calculated based on battery capacity and the observed SOC values. Since the observations for the SOC provide cumulative energy consumption, all comparisons and analysis in this study are conducted for cumulative results (Fig. 9e–f).

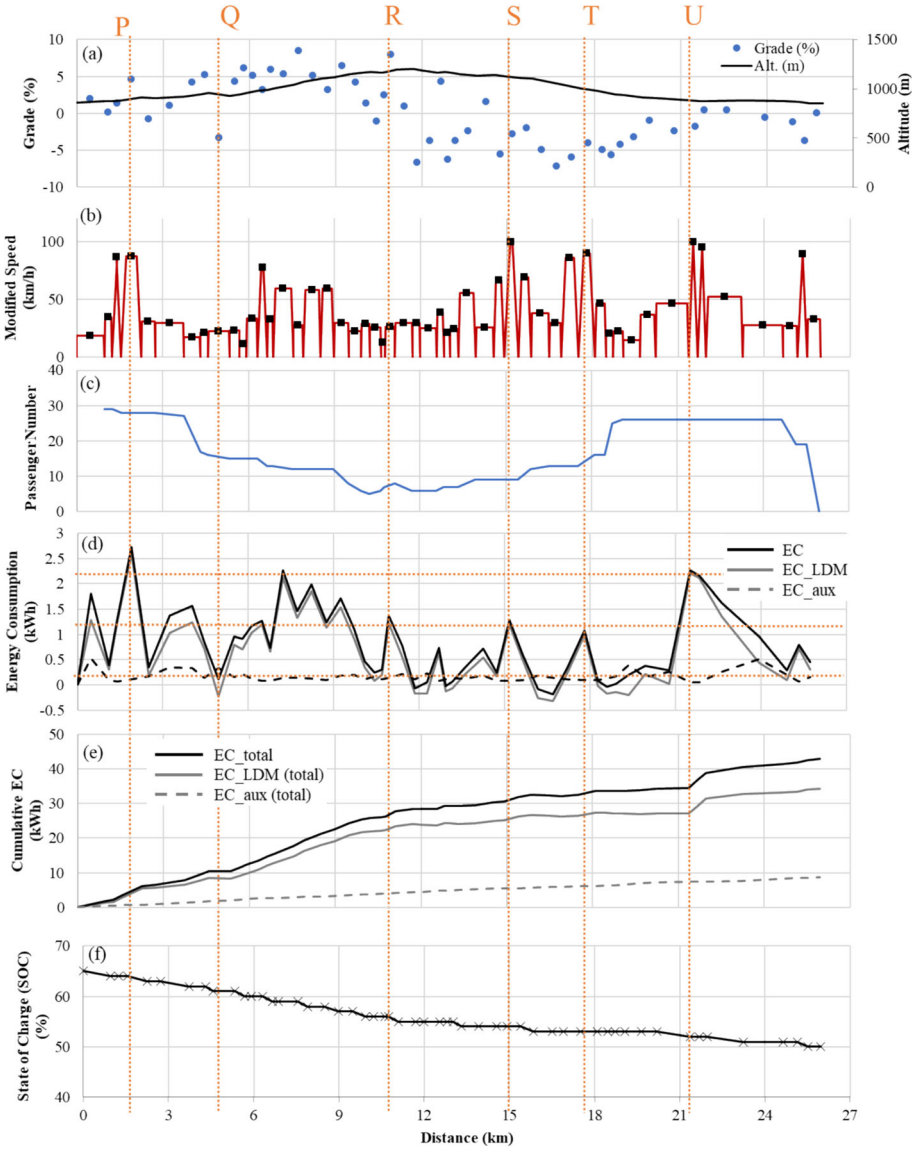


Fig. 9 BR-111-1 Route input data **a** Grade, **b** Modified speed profile, **c** Passenger number, **d** Inter-stop EC estimations, **e** Observed SOC, and **e** Route EC estimation

4.3 E-bus route EC estimation

The parameters used in E-bus EC calculation and the resulting cumulative EC profile are shown in Fig. 9 for BR-111-1. The mechanical EC is obtained from the E-bus EC estimation matrix using the grade, speed, passenger load, and stop distance values. The values are calculated for each inter-stop distance. The speed value is calculated based on time and distance difference between stop points, making use of the gathered data. The speed and acceleration profiling is conducted assuming 1.8 m/s^2 acceleration and deceleration as explained in Sect. 3.5. The parameters are inputted to the E-bus EC estimation matrix, and the EC estimation per km is obtained. Finally, the EC per km value is proportioned to the distance between stops. The auxiliary energy requirement is calculated based on the ambient temperature, and the total EC is determined as the sum of E_{LDM} and E_{aux}.

The obtained EC results for each inter-stop distance are shown in Fig. 9d, and the cumulative EC profile for BR-111-1 is shown in Fig. 9e. High speeds are observed for sections P, S, T, and U, and the altitude increases from section P to R and decreases from point R to U. The changes in the EC can be discussed based on the changes in these parameters. At point P, the speed is high, and the grade is high; therefore, an EC that reaches above 2.5 kWh is estimated. With the decreasing grade between point R and U, even though high speeds are observed, the EC is estimated to be below 1.5 kWh and mostly around 0.5 kWh. Finally, at point U, where the grade is almost zero, the high speed caused an increase in EC reaching up to almost 2.5 kWh.

4.4 Evaluation of E-bus use in PT services in Ankara

The E-bus EC estimation is performed for four cycles of BR-112 and three cycles for BR-111. Table 6 summarizes the details of the EC calculation. Since all the data is gathered from the operation of the same bus and the same driver, differences that can be caused by driver and bus are eliminated.

For BR-112, the highest E_{aux} per km is observed in journey 112-3 and 112-4 as 0.42 kWh and 0.44 kWh, respectively. The maximum EC per km is observed for the afternoon (112-3) and the evening peak (112-4). The difference in total EC between the afternoon journeys and the morning journeys is mainly due to the HVAC activity and the ambient temperature. For the high ambient temperature cases (38° C–36° C), the auxiliary EC is significant. The auxiliary

Table 6 Summary of EC calculation

Route-cycle	Cycle time	Route distance (km)	EC estimations				RMSE
			E_{LDM}	E_{LDM}/km	EC	EC/km	
112–1	06:40–08:18	31.54	29.68	0.94	32.66	1.04	1.08
112–2	08:20–09:56	30.87	24.60	0.80	28.88	0.94	1.25
112–3	15:05–16:43	30.25	24.70	0.82	37.94	1.25	0.98
112–4	17:05–19:04	30.77	24.23	0.79	37.88	1.23	1.43
111–1	15:05–15:58	25.81	34.21	1.33	42.99	1.67	1.15
111–2	16:25–17:15	25.74	33.54	1.30	42.14	1.64	1.88
111–3	18:10–19:00	25.71	40.83	1.59	47.47	1.85	1.99

energy requirement is 11.8 kW and 9.9 kW, which correspond to 13.24 kWh and 13.65 kWh for journeys starting at 15:05 and 17:05, respectively. All of the BR-111 journeys are in the afternoon. Therefore, they operate at similar ambient temperatures (37 ^{o}C–36 ^{o}C–33 ^{o}C). Although the third cycle has the least E_{aux}, due to the lowest ambient temperature, the highest EC is observed because high E_{LDM} is observed. This is attributed to the increase in the passenger load. As discussed earlier, the effect of passenger load increases with increasing grade. The difference in EC between BR-111 journeys is a maximum 4.48 kWh that corresponds to 0.17 kWh/km.

Compared to BR-112, the EC observed in BR-111 is significantly high. This is mainly the result of the effect of the road gradient. Since the total EC also takes the ambient temperature into account, the energy required for the vehicle motion (E_{LDM}) is considered for the comparison of the effects of the selected factors. It can be seen that up to a 206% increase in E_{LDM} per km can be observed for different routes. However, this cannot be attributed only to road gradient because, as discussed previously, the road gradient, passenger load, speed, and stop distance produce a combined effect on the E_{LDM}. The effect of other factors can be examined by comparing the E_{LDM} results of the same route. There is a 22% and 31% difference in E_{LDM} per km and EC per km values calculated for BR-112. Similarly, a 22% and 13% difference is observed in E_{LDM} per km and EC per km for BR-111. A higher difference is calculated for E_{LDM} compared to EC. The reason that less variance in EC is observed for BR-111 is that the observations are completed during the afternoon, and high temperature differences are not present. This shows the variability of the EC throughout the day and the effect of ambient temperature.

5 Evaluation of the model performance

The observed percent remaining battery is recorded to account for the observed energy consumption. Figure 9e shows the SOC data gathered through field observations for BR-111-1. In order to compare the estimated energy consumption and the observed results accurately, the cumulative EC is used in comparisons. The observed SOC values are normalized to start with zero energy consumption using the following formula. Where BC is the battery capacity, $\%SOC_{start}$ is the remaining percent battery at the start of the journey, and the %SOC is the remaining battery percent during the journey recorded at stop locations.

$$ObservedEC = \frac{BC \times (\%SOC_{start} - \%SOC)}{100}$$

The comparison of the EC estimation and the observed EC values for BR-111 are shown in Fig. 10 for the observed cycles. The results show that the calculated EC and the observed EC show significant correspondence. The calculated root mean square errors for each cycle are shown in Table 6. The maximum and minimum error is calculated for BR-111-3 as 1.99 and for BR-112-3 as 0.98, respectively. The main reason for the calculated errors is that the observed SOC is an integer. Since the SOC at the journey start of the journey cannot be precisely determined, the comparison of the observed and the calculated EC may show differences. However, as explained, these errors are acceptable.

BR-111 consists of high road grade differences; therefore, it is seen that regenerative braking occurs when the road grade is negative. This results EC to decrease at certain points. The observed data also resembles this result. To better illustrate the effect of regenerative braking with the decrease in slope; Fig. 11 is prepared. The distribution of EC/km is plotted for BR-111 routes. The decrease in the EC/km is observed when braking is performed. In

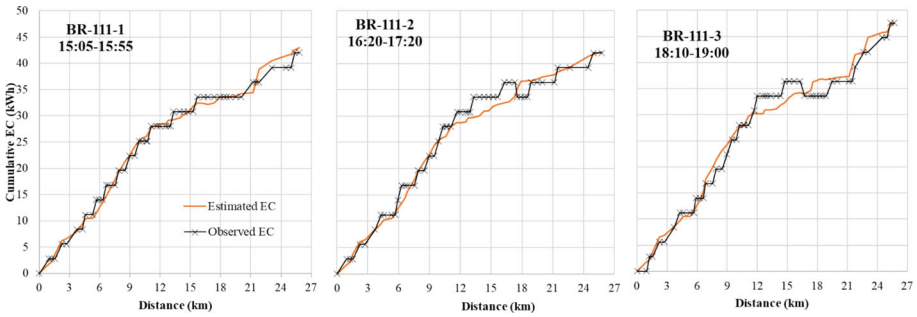


Fig. 10 BR-111 Comparison of estimated and observed EC

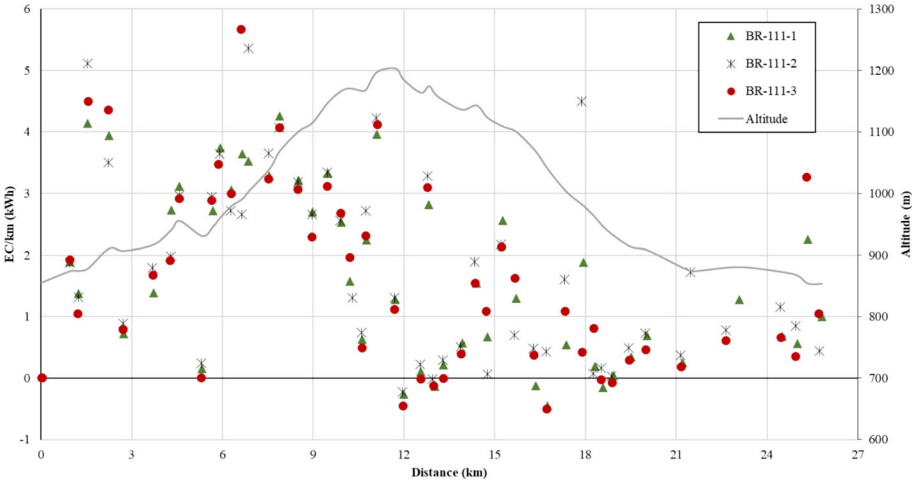


Fig. 11 EC/km distribution along BR-111 routes compared to the altitude

fact, at certain times the regenerative braking is dominating the EC related to motion that results in a negative EC that resembles energy gain.

Figure 12 shows the EC at BR-112 throughout the day. The bus covers 125.08 km in total. The ambient temperatures, passenger load and the speed of the vehicle is also shown to discuss the changes in EC. For the same routes, the road gradient and stop distance can be considered constant. The highest E_{LDM} is calculated for the first journey starting at 06:40 (112-1). The increase in E_{LDM} is a result of high passenger load. Finally, the overall daily EC value is compared to the values published by the manufacturer. The battery capacity is published as 280 kWh and the estimated range is 340 km. This shows that the manufacturer estimates 0.82 kWh EC per km. This is the EC calculated for the test case scenario. In the tests done during the actual operation of the buses, the observed EC ranged between 0.94k Wh/km and 1.85 kWh/km with an average value around 1.12kWh/km for BR-112 and 1.72 kWh/km for BR-111. Using the average value, the range can be estimated as 250 km for BR-112 and 1km for BR-111.

The daily performance of the E-bus operation is important when planning the operation and charging schedule. It is clear that the ambient temperature increases the EC mainly due

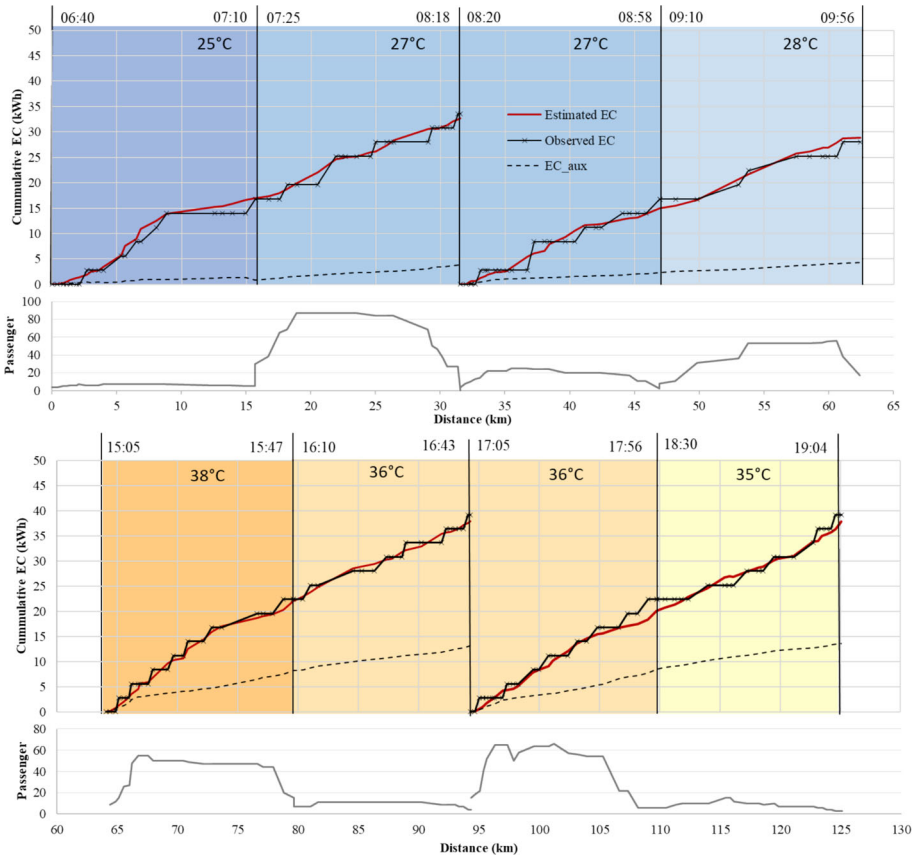


Fig. 12 Comparison of EC and passenger load for BR-112

to HVAC activity. When the ambient temperature is above 35 ^{o}C, the effect of HVAC is clearly observed (Fig. 12). The auxiliary energy requirement for 112-3 is almost three times the E_{aux} required for 112-1. If the morning peak and evening peak is compared, it can be seen that high passenger numbers are observed for the outbound direction in the morning and inbound direction in the evening. With similar passenger load and similar journey time, 112-3 requires 31% more energy to operate. This is the result of auxiliary EC. The least EC is observed for the journey starting at 08:20 (112-2) due to low ambient temperature values that correspond to 0.1 E_{aux} per km and low traffic condition. When the ambient temperature is close to the optimum temperatures (in the morning), other factors show their significance, as can be seen in the difference between morning journeys The journey starting at 06:40 has a higher EC compared to the journey starting at 08:20. Considering less HVAC operation and less traffic, one might expect lower EC early in the morning but due to the passenger load, the required mechanical energy increases. This shows that the difference in the overall EC cannot be attributed to the auxiliary load difference. The mechanical energy requirement should be investigated for the driving profile (traffic condition) and passenger load. It should be noted that the E_{aux} is directly related to driving time. Therefore, more stops, exposure to traffic congestion, high dwell time significantly affects the E_{aux} especially for long routes and extreme high/low ambient temperatures.

6 Conclusion and further recommendations

Planning the use of E-buses in public transportation systems can be challenging. The results show that even in the same day, with the same driver and bus, the EC can show significant differences. These fluctuations in the EC of an E-bus creates challenges in E-bus operation planning since the charging infrastructure is still not adequate and the battery capacity of the E-buses still need improvement. Therefore, until these infrastructural and technological advancements are completed, the E-bus deployment should be planned carefully, which is addressed by the proposed methodology in this study.

Factors affecting the performance of E-buses are stated in the literature, but these factors also include parameters that cannot be changed at the planning stage, such as parameters of the mechanical parameters of the bus or road infrastructure parameters. This study focuses on factors that can be taken into consideration during the planning phase and improved when necessary. These are determined as speed, road grade, stop distance and number of passengers. The effect of these factors were calculated for each variable and an electric bus energy consumption matrix was created. The impact of the selected factors is shown in this matrix. During these calculations, weight and front area values were used for the selected bus. When calculations need to be made for another bus, these values must be changed.

The ambient temperature highly affects the EC especially for hot summer days and cold winter days. This study focused on the summer results because the literature is limited for hot days. The effect of road gradient is inspected by considering two different routes with opposite route gradient properties. The results show that the EC estimation for an E-bus can be estimated by summing the values obtained from the E-bus EC estimation matrix and the auxiliary energy requirement. This tool can be of significant use in operation planning since the estimation provides acceptable results with only limited available data. The novelty of this study lies in the development of a flexible EC estimation framework that.

- Captures the effect of multiple operational and environmental factors.
- Provides practical insights into route and energy optimization for E-bus deployment in urban transit systems.
- Demonstrates a novel application of the bi-factor analysis to isolate and analyse the impact of factors like road gradient and passenger load.

Additionally, while many existing studies utilize longitudinal dynamic models, our work goes further by integrating these results into an actionable EC matrix. This matrix can be used for operational planning without requiring extensive computational resources.

The results obtained from this study provide useful information on the operation and route planning of E-buses include

- E-buses should be operated with minimum dwell time so that the auxiliary energy requirement is minimized.
- The distance between stops should be kept maximum and if possible the stops should be arranged such that the distance between stops is definitely greater than 250 m and preferably 500 m.
- High traffic has a significant effect on the EC for E-buses. Therefore, introduction of actions such as bus lanes to the network will be highly affective to minimize the EC.
- By monitoring the passenger load, the operating bus size can be optimized such that empty buses are eliminated.
- The energy contribution of auxiliary loads can surpass 50% of total EC on hot days.
- The EC estimation matrix we developed provides accurate predictions (average RMSE: 1.2%) when tested against field data.

- And finally, although altering the grade factor in cities by changing the bus route is not very likely, when new routes are created the grade factor can be considered. For the initial deployment stage, the routes with high route grades can be kept in background and other routes can be prioritized for E-bus deployment.

The limitations and further improvement directions of the study can be listed as;

- The E-bus EC estimation matrix is prepared for a single type of standard 12 m E-bus, but can be easily modified to be used with other buses
- Currently, there are limited studies that test the effect hot summer days (almost 40 $^{\circ}$C) for the e-bus operation.
- The winter conditions in terms of ambient temperatures is not tested
- The high traffic condition is not observed during the tests; therefore, the effect of high traffic should also be tested.
- By evaluating the energy consumption of the bus with only one driver, the variability is minimized, ensuring that any observed differences in EC is due to external factors rather than driver behaviour. However, this setup limits real-world applicability by not accounting for variations in driving styles and driver-induced energy consumption differences, reducing the generalizability of the results.

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Data availability Data will be made available on request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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