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The influence of inclement weather on electric bus efficiency: Evidence from a developed European network

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ABSTRACT

The daily operational capacity of an electric bus service is affected by many real-world factors, such as variations in weather, route characteristics, and traffic. Before bus operators electrify their fleets, they need to understand the effect inclement weather has on service stability, efficiency, and feasibility. Previous research on this topic is limited, developing models which are difficult to interpret, or physics-based theoretical models, which do not use real-world data and scenarios. To fill this research gap, this research applies a series of ordinary least squares (OLS) regressions to data from an established European electric bus operator to estimate the impact variation in weather conditions has on energy consumption, energy regeneration rates, charge cycles, speed of service, and vehicle emissions. The results show that higher wind speeds and lower temperatures positively correlate with energy consumption and negatively correlate with the total energy regeneration rate. This effect is especially pronounced at freezing temperatures.

1. Introduction

According to the Intergovernmental Panel on Climate Change (IPCC) in 2018 (Masson-Delmotte et al., 2018), anthropogenic CO_2 emissions must decline by 25% from 2010 levels by 2030, reaching net zero around 2050 to limit global warming to the 1.5 °C target set by the Paris Agreement.[1] This has encouraged the European Commission (EC, 2020) to raise the 2030 Greenhouse Gas (GHG) emission reduction target[2] from 40% to at least 55% compared to 1990. Moreover, the European Commission (EC, 2020) aim for Europe to be climate neutral by 2050. In 2020, road transport emissions were over 25% higher than in 1990 and accounted for a fifth of the European Union's (EU) total GHG emissions (EC, 2020). One reason for this was the slow uptake of alternate propulsion systems. For instance, in 2015, the transport sector had the lowest share of renewable energy, with only 6%. The European Commission (EC, 2020) states this must increase to around 24% by 2030 and identify electrification as one of the main development strategies they wish to pursue. Specifically, "the EU's strategy focuses on 1) increasing the transport system efficiency; 2) speeding up the deployment of low-emission fuels, and 3) speeding up the deployment of zero-emission vehicles" (Donkers et al., 2020).

Battery electric buses (BEBs) are a popular solution due to their zero tailpipe emissions and low noise pollution relative to traditional alternatives (Aldenius et al., 2022). However, range anxiety has been a significant barrier to the uptake of electric vehicles (EVs) (Zhang et al., 2021). As a result, accurate energy consumption prediction is necessary to design efficient and reliable electrified bus services (Wang et al., 2017; Li et al., 2021). Unfortunately, "energy consumption prediction is

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[1] IPCC, 2018: Global Warming of 1.5 °C. An IPCC Special Report on the impacts of global warming of 1.5 °C** above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty (Masson-Delmotte et al., 2018).

[2] European Commission, 2020. Communication from the Commission to the European Parliament, The Council, The European Economic and Social Committee and the Committee of the Regions, Stepping up Europe's 2030 climate ambition Investing in a climate-neutral future for the benefit of our people. Retrieved fromhttps://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0562here.

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challenging due to complicated driving cycles and a wide range of influential factors” (Chen et al., 2021).

Many factors have been considered when modelling the energy consumption of electric buses. Specifically: environmental conditions (e.g., ambient temperature), route characteristics (e.g., trip length, number of bus stops, and number of traffic lights), and dynamic traffic conditions (e.g., average travel speed and departure day of the week) (Li et al., 2021). In their study, (Abdelaty et al., 2021) noted that “the road gradient had the greatest impact on energy consumption among operational, topological, vehicular, and external parameters”. However, to the best of our knowledge, there has been little research on a) the impact of weather effects (such as rainfall and wind) on energy consumption and b) how the resulting energy consumption uncertainty affects operation stability, efficiency, and feasibility. Moreover, “amongst the existing research on EVs, relatively little has focused on electric buses” (Chen et al., 2021; Liu et al., 2021).

This research aims to fill these research gaps by investigating the impacts of rainfall, wind, and ambient temperature on operations stability, efficiency, and feasibility using data from an anonymised European source. Real-world data is valuable in analysing true service feasibility because it includes disruptions not necessarily captured by the theoretical “standard” case. It is essential for bus operators they understand how their electric buses will cope with deviations from the standard service routine; that is, the bus service may be feasible under average weather and traffic conditions, but it is important that the service remains feasible in abnormal cases too. Furthermore, policymakers require this information to improve their understanding of the problems electric bus operators face and what actions are required to facilitate the bus sector’s decarbonisation. The data set used in this study is very well suited to analysing these variations, as the bus service is operated in a demanding coastal area which frequently experiences low temperatures, heavy rain, and high wind speeds along a route which includes several steep hills. To analyse the effect of inclement weather on service stability, efficiency, and feasibility, this study uses a series of standard ordinary least squares (OLS) regressions to determine the impact of wind, rain, and temperature on several key performance indicators (e.g., energy consumption, total regeneration rate, service speed, and vehicle emissions).

The remainder of this paper is organized as follows: Section 2 reviews and compares the findings of the previous literature in this space; Section 3 presents our data sources and briefly introduces the analytical methodology; Section 4 explains the results of our research and discusses our findings; and finally, Section 5 concludes.

2. Previous literature

Extreme cold and hot ambient temperatures have been shown to reduce the efficiency of BEBs, as well as age their batteries. Al-Zareer et al. (2017) suggested that the optimum temperature range for lithium-ion battery operation was 25–40 °C. However, multiple optimal ranges have been suggested. For example, Wang et al. (2017) analysed the fuel consumption data of 68 BEBs in Aichi Prefecture, Japan, and estimated an optimal temperature of 17.5 °C, also concluding that **“the relationship between energy efficiency and ambient temperature presents an asymmetrical “U” shape” (with colder temperatures having a larger negative affect). Whereas Liu et al. (2018) concluded that “the most economic energy efficiency was achieved in the range of 21.8–25.2 °C”, despite using the same case study. The American Automobile Association (AAA) had initially found that for broad electric vehicles, when temperatures dip to around minus six degrees Celsius, the average driving range decreases by 41%. So, for every 160 km of combined urban and motorway driving, the range would be reduced to 95 km.[3]

(Donkers et al., 2020) used a physics-based model to estimate the impact of wind speed, wind direction, and ambient temperature on a BEB’s energy consumption for different speeds (30 km/h and 130 km/h) and different driving styles (Eco, Normal, and Aggressive). They found that the relative influence of the ambient temperature is extremely high at low driving speeds (30 km/h) and significantly lower at high driving speeds (130 km/h). Moreover, the optimal ambient temperature for energy consumption at low driving speeds is 20 °C, whereas, at higher speeds, the highest efficiency is gained at high temperatures (due to lower aerodynamic drag). (Wang et al., 2018) had also included aerodynamic drag in their physics-based model, emphasising its importance by stating that a reduction in ambient temperature from 30 °C to 0 °C has the effect of increasing rolling resistance by as much as 30%. Jaguemont et al. (2016) found that EV batteries suffer performance losses and ageing in cold weather, concluding that “the low-temperature performance of Li-ion cells can be attributed to several factors, including the motion of lithium ions in the electrolyte solution (electrolyte conductivity), cell design, electrode thickness, separator porosity and separator wetting properties”. Battery ageing has two principal effects: impedance rise and capacity fade (Zhang and White, 2008). Bloom et al. (2001) and Wright et al. (2002) show that calendar ageing (defined as “irreversible damage to a cell’s capacity caused when the battery is not in use”) is more marked at higher temperatures than under ambient-temperature conditions. Moreover, cycle ageing (defined as “irreversible damage to a cell’s capacity caused when the cell is operating, either charging or discharging”) is amplified at higher temperatures, leading to “greater charge capacity loss and impedance rise than observed at ambient temperatures” (Ping et al., 2014).

Variance in ambient temperature indirectly increases the energy consumption of BEBs by increasing the energy demand of climate control (air conditioning/heating). This effect is often large since (Kessler and Bogenberger, 2019) found that for their sample of 60,000 trips in Germany, the share of total energy derived from climate control had a median value of 42% and 0.25 percentiles at 29% and 49%. Zhou et al. (2016), and others measured the effect of air conditioning under nearly-worst-case scenarios (Summer in Macao with the system set to maximum) and found that it contributed to increased energy use of approximately 10–25% depending on the loading, traffic, and ambient conditions. Moreover, Liu et al. (2018) estimated a mean of 9.66% electricity could be saved by eradicating unreasonable EV auxiliary loads.

Rainfall and wind can impact energy consumption by affecting frictional and rolling resistance, respectively. However, previous research suggests that both variables have a negligible effect on the energy consumption of BEBs unless they take extreme values. For example, Li et al. (2021) found the wet-dry condition to be the least important variable in their study (which accounted for dynamic traffic conditions (e.g., average speed), route characteristics (e.g., number of bus stops), and environmental conditions (e.g., ambient temperature)). Specifically, their results showed that “the average electricity consumption per kilometre in wet conditions was 1.14 kWh, compared to 1.18 kWh consumed per kilometre on average in dry conditions.”.

The impact of wind also depends on the amount of cover on the route (such as tall buildings or nearby trees) and the direction of the wind in relation to the direction that the bus is moving. Beckers et al. (2019) attempted to include the effects of relative wind direction in their physics-based energy consumption prediction model by using “coast-down measurements” rather than Computational Fluid Dynamics (CFD). However, they conclude that their aerodynamic model would be improved by considering wind velocity and relative wind direction. Wang et al. (2018) used a formula to model aerodynamic force, which implied high driving speeds intensify the effect of headwinds. During their small sample of 30 driving tests (used to validate their energy consumption prediction algorithm), the influence of wind was very small. Donkers et al. (2020) also found that wind speed had considerably more influence on energy consumption at higher driving speeds.

[3] The report is availablehttps://www.aaa.com/AAA/common/AAR/files/AAA-Electric-Vehicle-Range-Testing-Report.pdfhere

However, Donkers et al. (2020) included energy consumption estimations for much more extreme weather profiles than (Wang et al., 2018), leading to results which suggested that, even at low driving speeds, extreme headwinds exceeding 65 km/h (90 km/h) can double (triple) energy consumption.

Energy consumption uncertainty due to variance in relevant weather-related variables can have a large negative impact on operation feasibility and cost due to the range requirements of inflexible route characteristics (e.g., charging infrastructure) and timetabling. Regarding ambient temperature, Rastani et al. (2019) found that low temperatures reduce battery efficiency and cause performance loss. Subsequently, routing plans can become unfeasible (the number of vehicles required to complete the service may increase, and it might become impossible to serve all customers using an EV fleet) if they are not sufficiently "temperature-sensitive." Benoliel et al. (2021) created a tool to investigate the optimal split between depot charging and opportunity charging for transit networks. Their research suggested that variables which affect BEB range (such as ambient temperature, passenger loading, and drive cycle aggressiveness) can double the minimum/optimal system cost (bus purchase, infrastructure purchase, and operating costs) because a "one size fits all" system will have to be designed around a worst-case scenario. Essentially, low energy efficiency reduces vehicle range, which means either more opportunity chargers or more buses are required to complete the service. Generally, it is considered economical to charge fleets overnight at the depot while electricity prices are low and there is time to complete a full charge. However, if the vehicle State of Charge (SOC hereafter) depletes too quickly, BEBs must be charged at the depot during the day. An internal combustion engine (ICE) in the same situation can refuel within 10 min and return to service, whereas a BEB can take 2–4 h to recharge fully. Thus, an operator's fleet either needs to include spare fully charged BEBs, or a small number of ICEs, in case of operational emergencies. As a result, the literature presents a trade-off between feasibility and cost, i.e., it is costly to design a bus system that ensures all services will be feasible when the fleet is fully electrified.

Variance in the energy consumption of BEBs also affects costs by increasing energy demand. Quarles et al. (2020) use a base-case electricity cost of 0.07$/kWh. Hence, using this value, the 0.04 kWh/km impact of dry surface conditions proposed by Li et al. (2021) would be associated with a 0.0028$ increase in electricity costs per kilometre. Moreover, additional opportunity charges during the day can trigger higher demand charges, especially if the timetable requires multiple opportunity charges to be completed simultaneously. Aamodt et al. (2021) use the example that if "3 buses charge simultaneously overnight at their max 80 kW for multiple hours", this would be associated with a peak demand of 240 kW. Assuming a median demand charge of $10/kW, the corresponding demand charge for this month would be $2,400. This is a significantly lower figure than if 2 buses were required to use the fast charger simultaneously at 450 kW. For example, even if peak demand is measured over 15-min intervals and the opportunity charges only last 7 min, the peak demand would be 420 (2 × 450 kW × 7 min/15 min), resulting in a monthly demand charge of $4,200.

In summary, there are few articles which assess the impact of inclement weather on the daily operation of electric bus services and most of the papers investigating this topic use either physics-based models or machine learning. Physics-based models don't use real-world data, and this prevents them from providing an accurate prediction for how a bus service would be disrupted by extreme weather conditions. For instance, they do not incorporate the indirect effect of inclement weather on service operations due to traffic, road closures, and increased auxiliary load from heating, ventilation, and air conditioning (HVAC) systems. Machine learning methods are effective at providing accurate energy consumption predictions. However, the results are specific to each case study, and it is difficult to interpret the impact of changes to individual weather variables, given the black-box nature of the methodology. There needs to be more research into the impact of inclement weather on service stability, efficiency, and feasibility, which utilises real-world data and provides interpretable results.

3. Data sources and analytical methodology

3.1. Electric bus data

In the following sections, we present several distinct presentations of unique data and estimations designed to specifically investigate the operation's stability, efficiency, and, finally, feasibility. All data has been anonymized to protect the identity of the provider. In Fig. 1, we observe the total hourly distance driven. Throughout 2019, the average was 16.7 km, while in 2020, the average was 19.1 km per hour. This is largely considered a signal of increased operational efficiency over time. There is also evidence of some abnormal data behaviour in the period through mid-April and May 2020, where the estimates vary quite substantially. There is evidence in related news searches of a substantial road alteration that required partial route closure. This led to a slight differential in route behaviour which we have considered throughout this analysis[4].

In Fig. 2, we observe the odometers of four random electric buses within the sample that has been presented, designed to illustrate the variety of situations. Bus 1 presents one of the earlier buses that entered service. As can be seen from the data, the bus entered just a short number of servicing periods, with evidence of one prolonged period of servicing in June 2020. Bus 2 presents an unusual scenario, where the bus entered service in a traditional manner. However, between June 2019 and April 2020, the bus is unfortunately out of service. The reasons for this have not been made available. Bus 3 presents a traditional service scenario; however, there is a prolonged stoppage between July 2019 and September 2019. No data for this service was made available after 31 December 2019. Bus 4 entered service in July 2019 and has worked continuously since with a few brief servicing periods. Several other similar data series were available. However, for both anonymity and brevity, only the following have been presented. In Fig. 3, we find the trend of particles' net result, which is calculated based on company emission settings. Particles net result = particles produced - particles saved (Units: g). Particle Number (PN) emissions have been studied intensively in academia and industry because of the adverse effects of ultra-fine PM emissions on human health and other environmental concerns. Gasoline Direct Injection (GDI) engines are known to emit a higher number of PN emissions (on an engine-out basis) than Port Fuel Injection (PFI) engines due to the reduced mixture homogeneity in GDI engines. Euro 6 emission standards have been introduced in Europe (and similarly in China) to limit PN emissions from GDI engines. There is limited evidence to suggest any significant improvements or disimprovements during the period analysed.

We next present data relating to battery regeneration and performance. In Fig. 4, we observe the regeneration rate, the percentage of regenerated energy for a vehicle.[5] There is evidence to suggest that the rate increases over the first year, from an average of 37% to 39%; however, it falls to 34% in late 2019.

In Fig. 5, there is also evidence of increased charging time per hour stopped throughout 2019. At present, we are seeking further information as to whether there are any technical explanations for why this situation occurred. There does not appear to be an obvious explanation within the data presented[6]. The total State of Charge (SOC) is also

[4] In the associated online appendices, data is presented relating to the energy charged, NO_x net result, the average number of charging sessions.

[5] Estimated as the ratio of energy regenerated while driving divided by energy consumed. The subsequent value is then scaled through multiplication by one hundred.

[6] Data relating to total driving time, total time idling, and total time both in and not in service are presented in the Online Appendices.

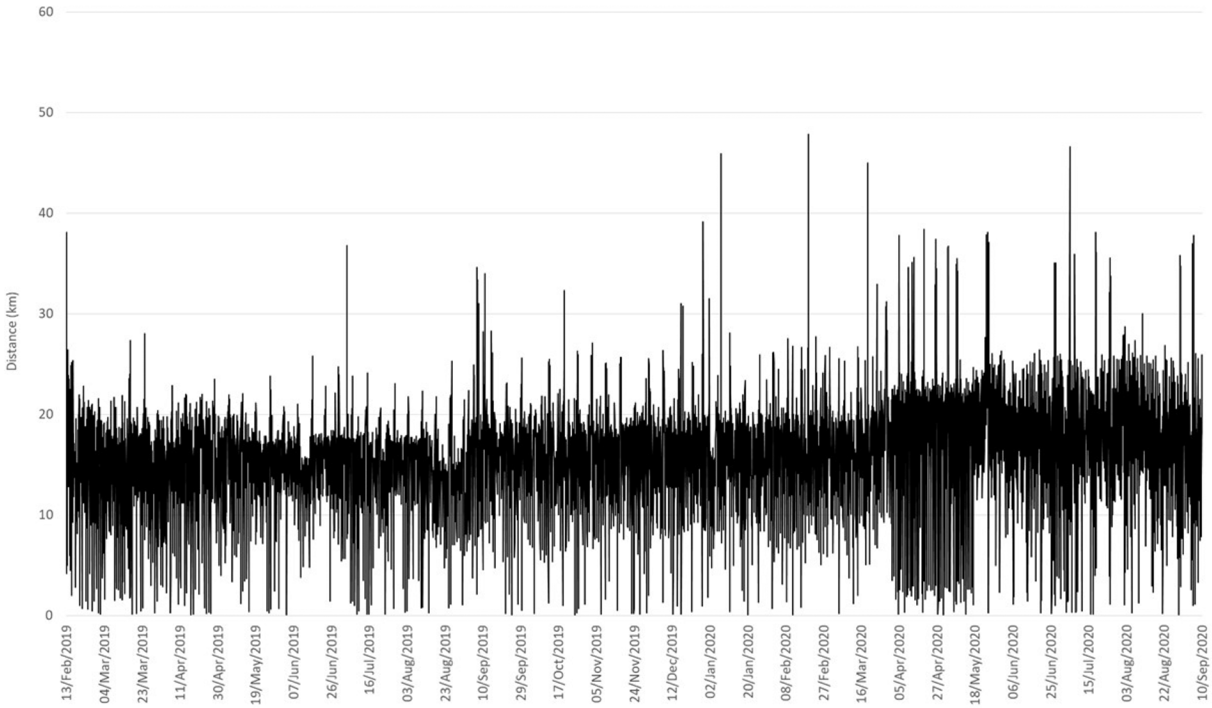

Fig. 1. Distance driven in kilometres (hourly data) Note: Data relating to the bus service is anonymized.

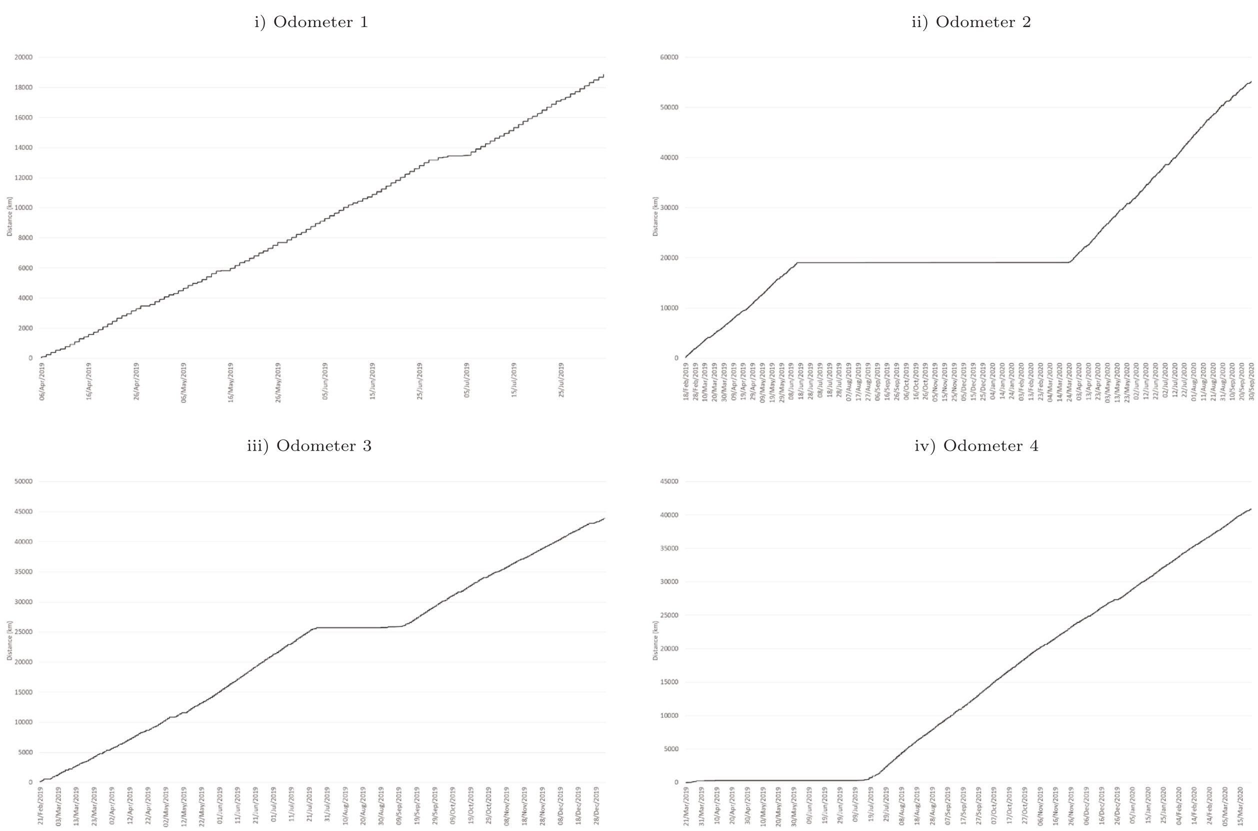

Fig. 2. Odometers of the anonymous buses used in the sample (hourly data) Note: Data relating to the bus service is anonymized.

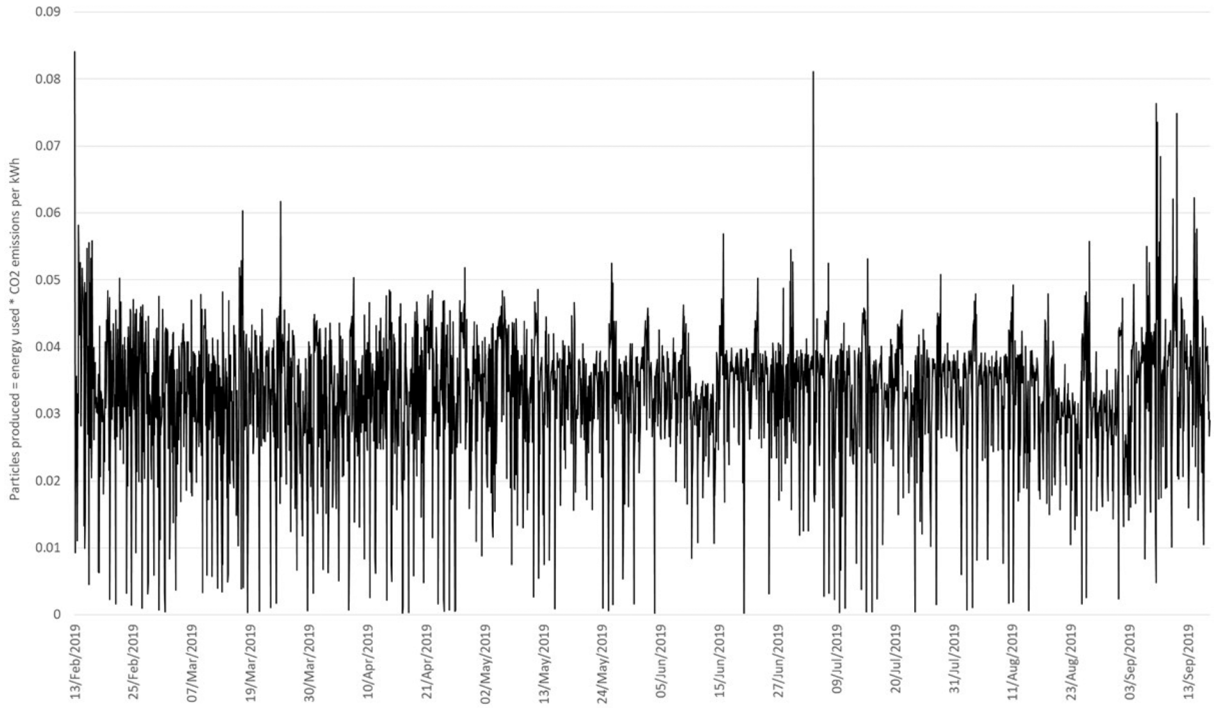

Fig. 3. Particles net result Note: Particles net result is calculated based on company emission settings. Particles net result = particles produced – particles saved. Units: g. Data relating to the bus service is anonymized.

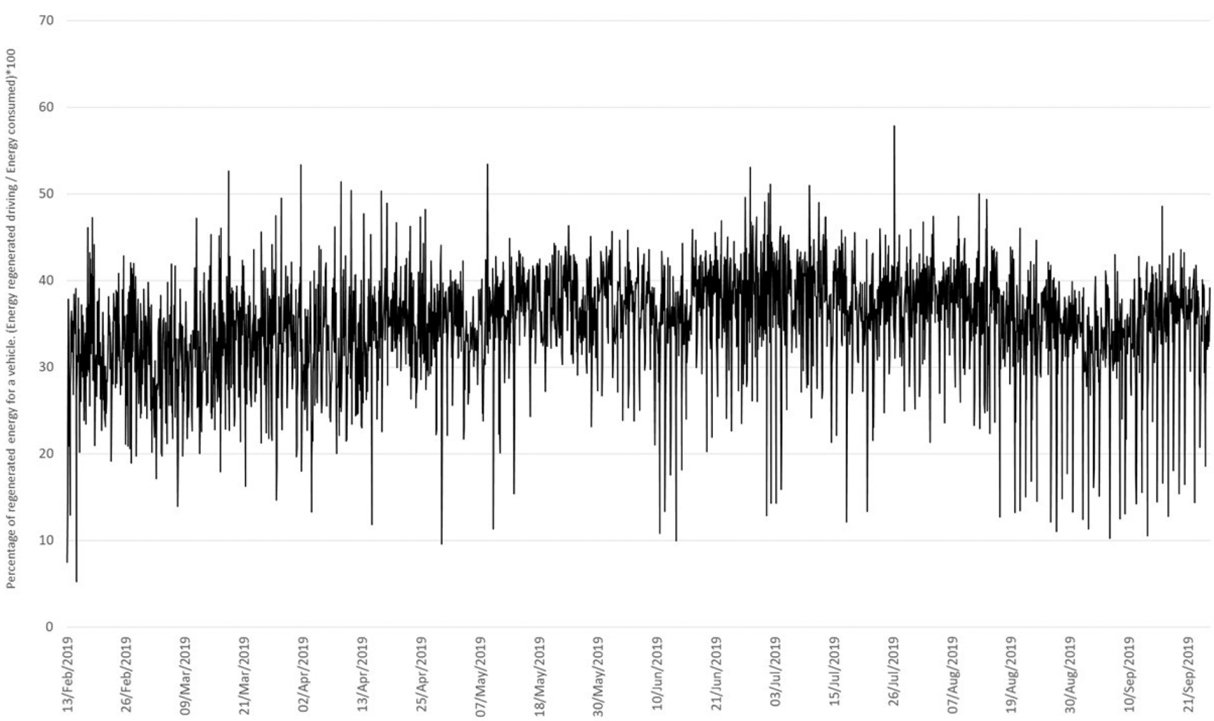

Fig. 4. Regeneration rate Note: Regeneration rate is the percentage of regenerated energy for a vehicle. (Energy regenerated driving/Energy consumed)*100. Data relating to the bus service is anonymized.

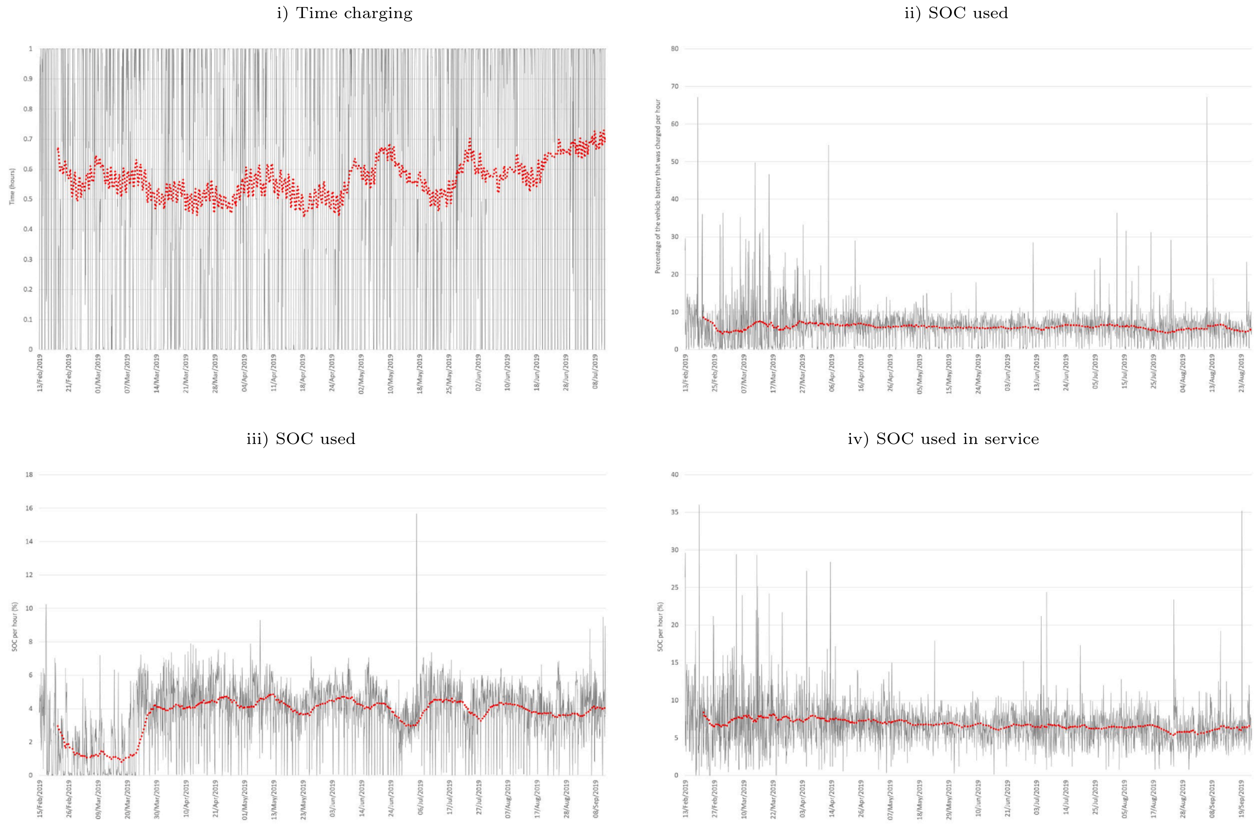

Fig. 5. Charging and state of charge statistics Note: Time charging is the time the vehicle was charging. No positive speed or energy readings and no idling state. Data relating to the bus service is anonymized. SOC charged is the percentage of the vehicle battery that was charged. SOC used is the percentage of the battery used by the vehicle - both in service and out of service. SOC used = SOC in service - SOC not in service. SOC used idling is the percentage of the battery used while the vehicle was idling. Regenerated energy is included in this calculation. SOC used in service is the percentage of the battery used while the vehicle was in service. SOC used in service is the percentage of the battery used while the vehicle was in service. Data relating to the bus service is anonymized. The sequenced red bullet points represent the 72-h moving average representing a three-day trend.

presented in Fig. 5; we can identify that there was evidence of particular improvements in efficiency. We observe the total SOC used and the SOC used idling, the SOC both in service and out of service, respectively. SOC is the level of charge of an electric battery relative to its capacity. The units of SOC are percentage points where 0% indicates empty, and 100% indicates that the battery is full. SOC is normally used when discussing the current state of a battery. In a battery electric vehicle (BEV), hybrid vehicle (HV), or plug-in hybrid electric vehicle (PHEV), SOC for the battery pack is the equivalent of a fuel gauge[7]. The data presented indicate increased efficiency over time, where the red bullet points represent the 72-h moving average as a representation of a three-day trend. Although several outlier events exist, developing a less volatile operation is immediately evident, albeit there is evidence of less SOC achieved each hour. Please note that the accumulation of SOC is of importance here. While a bus is perhaps parked, it obtains SOC hourly. It appears this operation had attempted to obtain too much SOC in too short a period, which can also lead to significant long-term depreciation.

3.2. Key weather statistics

We first present an overview of the real-world data of an anonymous electric bus company before then providing a full estimation of our proposed network inclusive of such available information, available traffic data, factory-provided technical specifications, and hourly weather data for the period under observation. One of the first required tasks to be completed was the merger of this hourly technical data and hourly weather data[8].

In Table 1, we observe summary statistics of the anonymous regional weather data used within this analysis. Due to strict confidentiality arrangements, we will not disclose information relating to the specific region apart from the note that it is located in Europe. The above variables specifically represent Precipitation Amount (mm), Air Temperature (°C), Wet Bulb Temperature (°C), Dew Point Temperature (°C), Vapour Pressure (hPa), Relative Humidity (%), Mean Sea Level Pressure (hPa), Mean Wind Speed (kph) and Predominant Wind Direction (degrees). Data has been presented as divided by each seasonal average. We can see that the average hourly rainfall throughout the period was 0.13 mm per hour, with substantially lower rainfall experienced in the summer (0.06 mm) and above-average levels in the autumn and winter (0.17 mm and 0.16 mm, respectively). The average hourly air temperature is 11.66 °C with a minimum level of 0.60 °C and a maximum of

[7] It is important to mention that state of charge, presented as a gauge or percentual value at any vehicle dashboard, especially in plug-in hybrid vehicles, may not be representative for a real level of charge. In that particular case, some noticeable amount of energy stored in the electric battery is not shown on the dashboard, and it is reserved for hybrid-work operations. It permits a vehicle to accelerate with electric motor(s) mainly using battery energy, while the engine serves as a generator to recharge the battery to the minimum level needed for such operation.

[8] The above data is based on an anonymized region in which the electronic bus services had operated. The data has been presented in its raw format, obtained from a reputable source with government oversight, representing hourly rainfall in mm for the entire period at a stationary point.

Table 1
Summary statistics relating to modelled weather data.

Total									
	Prec.	Air Temp	W.B. Temp	D.P. Temp	V.Press.	Humidity	Sea Press.	Wind Speed	Wind Dir.
Mean	0.13	11.66	10.34	8.94	11.79	83.52	1,013.81	23.85	194.93
Variance	0.30	11.16	11.45	15.61	9.39	105.36	141.97	169.13	7,968.17
Skewness	8.51	−0.10	−0.12	−0.19	0.25	−0.57	−0.53	0.73	−0.46
Kurtosis	103.60	−0.54	−0.71	−0.69	−0.67	−0.27	0.58	0.33	−0.82
Minimum	0.00	0.60	0.30	−2.50	5.10	42.00	969.30	1.85	10.00
Maximum	12.50	21.80	18.50	18.40	21.10	100.00	1,048.60	85.19	360.00

Spring									
	Prec.	Air Temp	W.B. Temp	D.P. Temp	V. Press.	Humidity	Sea Press.	Wind Speed	Wind Dir.
Mean	0.14	9.04	7.74	6.12	9.60	82.15	1,014.22	27.54	180.05
Variance	0.23	4.08	4.82	8.83	3.64	114.27	165.53	219.65	7,744.27
Skewness	5.93	−0.42	−0.35	−0.32	−0.05	−0.41	−0.36	0.56	−0.23
Kurtosis	44.15	0.45	−0.57	−0.85	−1.08	−0.58	−0.18	−0.25	−1.19
Minimum	0.00	0.80	0.30	−2.50	5.10	46.00	978.00	1.85	10.00
Maximum	6.00	16.70	13.00	11.60	13.70	99.00	1,045.70	79.64	360.00

Summer									
	Prec.	Air Temp	W.B. Temp	D.P. Temp	V. Press.	Humidity	Sea Press.	Wind Speed	Wind Dir.
Mean	0.06	13.60	12.04	10.56	13.02	82.03	1,016.16	18.48	199.13
Variance	0.10	8.30	8.05	11.10	7.83	101.29	57.79	80.47	8,795.78
Skewness	11.03	−0.30	−0.28	−0.32	0.07	−0.57	−0.23	0.31	−0.43
Kurtosis	159.91	−0.08	−0.43	−0.46	−0.73	−0.13	0.59	−0.39	−0.81
Minimum	0.00	4.10	3.40	−0.90	5.70	42.00	987.60	1.85	10.00
Maximum	6.70	20.70	17.60	17.40	19.90	98.00	1,035.10	50.00	360.00

Autumn									
	Prec.	Air Temp	W.B. Temp	D.P. Temp	V. Press.	Humidity	Sea Press.	Wind Speed	Wind Dir.
Mean	0.17	13.68	12.55	11.50	13.79	86.65	1,012.70	23.43	205.24
Variance	0.47	5.88	6.40	9.03	6.54	79.40	113.63	114.80	6,589.67
Skewness	7.82	−0.96	−0.91	−0.82	−0.42	−0.71	−0.07	0.38	−0.79
Kurtosis	80.65	1.17	0.64	0.31	−0.41	0.01	−0.65	−0.32	−0.12
Minimum	0.00	2.50	2.10	1.30	6.70	53.00	981.40	1.85	10.00
Maximum	10.40	19.30	17.60	17.30	19.80	99.00	1,037.90	57.41	360.00

Winter									
	Prec.	Air Temp	W.B. Temp	D.P. Temp	V. Press.	Humidity	Sea Press.	Wind Speed	Wind Dir.
Mean	0.16	8.75	7.54	6.03	9.53	83.07	1,007.90	27.54	205.52
Variance	0.23	4.26	4.85	7.85	3.37	90.07	278.02	213.31	8,268.20
Skewness	5.21	−0.98	−0.36	−0.04	0.27	−0.39	0.10	0.31	−0.58
Kurtosis	42.08	1.16	−0.10	−0.78	−0.60	−0.75	−0.43	−0.55	−0.53
Minimum	0.00	0.60	0.30	−1.70	5.40	49.00	969.30	1.85	10.00
Maximum	7.60	13.80	13.60	13.50	15.40	98.00	1,048.60	85.19	360.00

Note: The above table represents the summary statistics of the anonymous regional weather data used within this analysis. Due to strict confidentiality arrangements, we will not disclose information relating to the specific region apart from the note that it is located in Europe. The above variables specifically represent Precipitation Amount (mm), Air Temperature (°C), Wet Bulb Temperature (°C), Dew Point Temperature (°C), Vapour Pressure (hPa), Relative Humidity (%), Mean Sea Level Pressure (hPa), Mean Wind Speed (kph) and Predominant Wind Direction (degrees).

21.80 °C during the analysed period. For methodological robustness, within this analysis, we also considered the wet bulb temperature (average hourly level of 10.34 °C with a minimum level of 0.30 °C and a maximum of 18.50 °C) and the dew point temperature (average hourly level of 8.94 °C with a minimum level of −2.50 °C and a maximum of 18.40 °C). Using these additional temperature metrics provided no deviation in presented results, and for brevity, results and graphics are not presented; however, they are available upon request. Summary statistics relating to vapour pressure, humidity and sea pressure are presented, although, after significant consideration, no significant effects were identified, although the variables are considered within the methodological structures. Simulation data considers the final variables surrounding wind speed (kph) and wind direction (degrees) to be significantly influential. The average hourly wind speed is 23.85 kph, with a minimum value of 1.85 kph recorded and a maximum value of 85.19. Seasonal differentials are identified with average hourly levels of 27.54 kph in the spring, 18.48 kph in the summer, 23.43 kph in the autumn and 27.54 kph in the winter. Upon a thorough analysis of many international electric bus networks, a substantial influence was identified with regard to temperature effects, particularly that of low temperatures; however, many network reports identified that there was not enough weight allocated to the effects of wind speed and its influence upon both range depreciation and range anxiety[9]. We utilised an ordinary least squares (OLS) specification to model the relationships between the key structural and weather-based data upon the performance of the electric bus network, such as speed of service, the efficiency of the

[9] Figures presenting the time series of weather data is presented in part B of the Online Appendices.

charging process, emissions, and an estimation of energy consumption under average time-varying weather conditions as presented. estimated as below:

$$\Delta M_t = \alpha + M_{t-n} + \beta_1 rain + \beta_2 wind + \beta_3 temp + D_t freeze + e_t \tag{1}$$

where M_t represents a separated methodological structure incorporating the effects of rain, wind, and temperature, respectively. D_{freeze} represented a dummy variable that takes the form of unity when freezing temperatures are present. The dependent variables examined relate to average speed, average speed in service, time driving, time in service respectively, charge cycles, and the state of charge generated, respectively. The estimation structure is revised to incorporate CO_2 net result, NO_x net result, and particle net result when considering the same estimated weather effects upon emissions statistics, respectively. In the final set of analyses, we estimate the effects of weather on the energy usage of the electric bus network and adapt the dependent variable to represent energy consumed when driving, energy consumed when idling, total energy, and for examination upon the energy regeneration rate, we focus upon the total energy regeneration rate and energy regeneration when driving, respectively. The lag order (n) of the respective dummy variables is determined by the Akaike Information Criteria (AIC).

4. Results and discussion

This section presents the relationship between the weather and various electric bus performance indicators. These bus performance indicators have been grouped into three categories: energy consumption, energy consumed, and energy regenerated.

4.1. Weather effect on energy consumption

In Fig. 6, we observe the number of charge cycles with respective temperature and rainfall levels. While accounting for several outliers within the dataset that can be largely attributed to servicing periods, there is a clear increase in the number of hourly charging cycles during the winter months, synonymous with increased depreciation and an increased necessity to recharge during periods of cold weather. Driving range and equivalent fuel economy reductions slightly differ due to the temperature dependency of both the recharge allocation factor (RAF) and battery discharge capacity: a) On average, an ambient temperature of 20 °F (−6.7 °C) resulted in a 12% decrease of combined driving range and an 8% decrease of combined equivalent fuel economy; and b) on average, an ambient temperature of 95 °F (35.0 °C) resulted in a 4% decrease of combined driving range and a 5% decrease of combined equivalent fuel economy (when compared to testing conducted at 75 °F (23.9 °C)). Such evidence can also be observed with regards to CO_2 emissions as presented in Fig. 7; however, there is little evidence to present a sustained increase in emissions except for a sharp increase in short-term trends of emissions growth in the period through January and February 2020, when compared to that of November and December 2019. CO_2 net result in this context is calculated based on company emission settings, which indicates that CO_2 net result is simply equal to CO_2 produced less CO_2 saved.

In Fig. 8 we observe energy consumption when driving, energy consumption in service (all modes once the bus has been turned on) and overall energy consumption (inclusive of charging states), respectively. There is clear evidence in all presented cases of an increase in energy consumption during the autumn and winter periods, in line with sharp depreciation in temperature. Immediately, during March 2020 and thereafter, there is evidence of a sustained reduction in energy

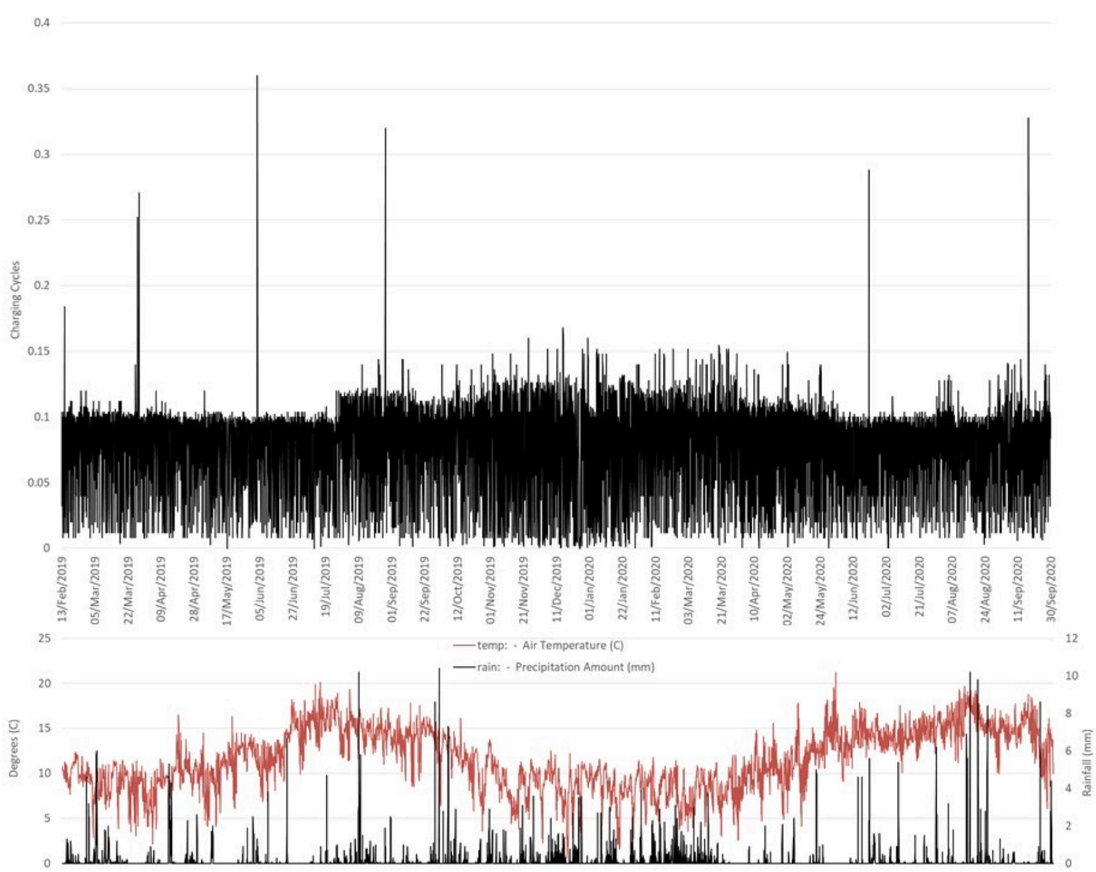

Fig. 6. Charge Cycles Note: The above temperature and rainfall data is based on an anonymized region in which the electronic bus services had operated. The data has been presented in its raw format and obtained from a reputable source with government oversight. Data relating to the bus service is anonymized.

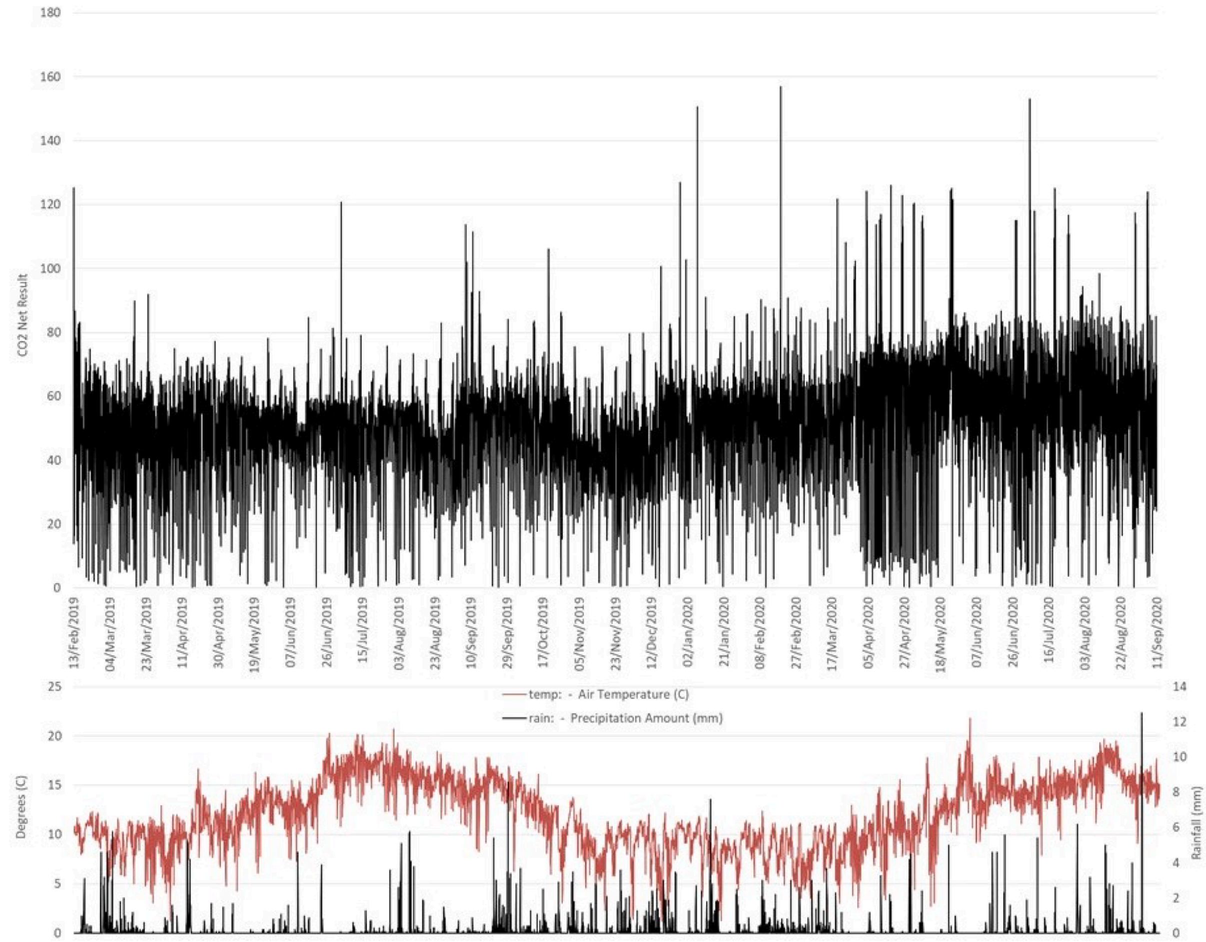

Fig. 7. CO_2 net result. Note: CO_2 net result is calculated based on company emission settings. CO_2 net result = CO_2 produced - CO_2 saved. Units: kg. The above temperature and rainfall data are based on an anonymized region in which the electronic bus services had operated. The data has been presented in its raw format and obtained from a reputable source with government oversight. Data relating to the bus service is anonymized.

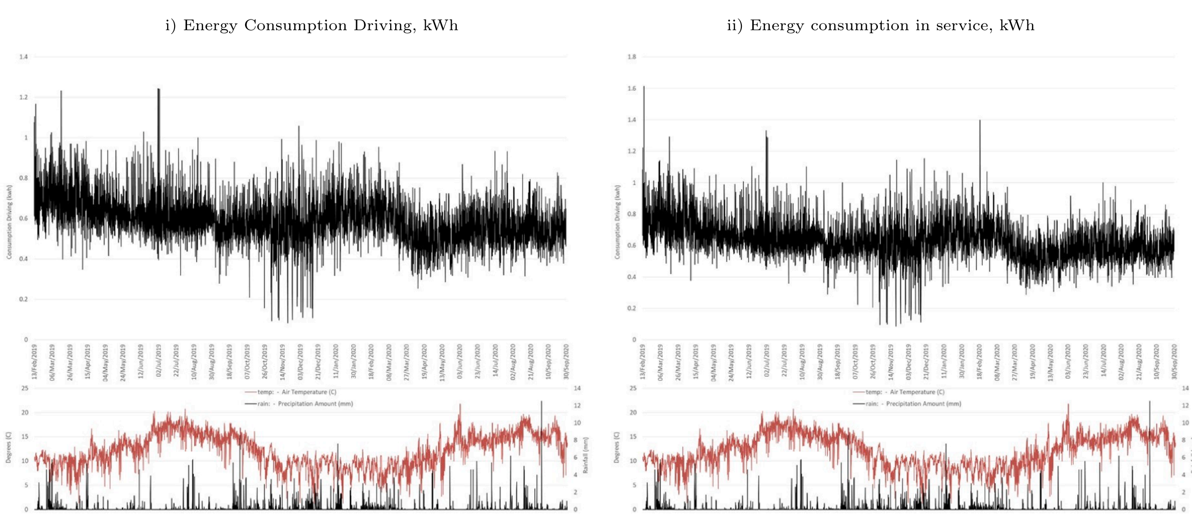

Fig. 8. Energy consumption statistics, kWh. Note: Consumption driving indicates total energy consumption while the vehicle is driving. Units: kWh. The above temperature and rainfall data are based on an anonymized region in which the electronic bus services had operated. Consumption in service indicates total energy consumption while the vehicle is in service. Energy consumed while driving indicates the total energy consumed while the vehicle was driving, and energy was positive. The data has been presented in its raw format and obtained from a reputable source with government oversight. Data relating to the bus service is anonymized.

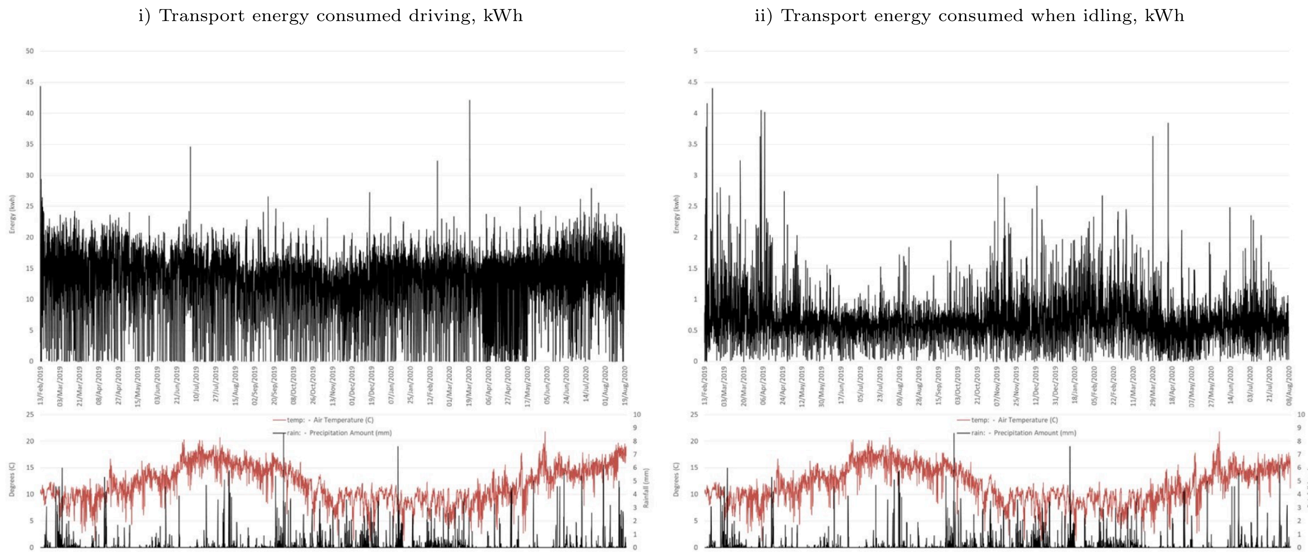

Fig. 9. Transport energy consumed driving and idling, kWh. Note: Energy driven indicates the total energy consumed while the vehicle was driving. Energy driven = energy consumed driving - energy regenerated driving. The above temperature and rainfall data are based on an anonymized region in which the electronic bus services had operated. Energy idled indicates the total energy consumed while the vehicle was idling. The above temperature and rainfall data are based on an anonymized region in which the electronic bus services had operated. The data has been presented in its raw format and obtained from a reputable source with government oversight. Data relating to the bus service is anonymized.

consumption. However, in the examined twelve months period, there is broad volatility of results largely indicative of substantial inefficiencies during the development of the electric bus network.

The total amount of energy, as measured in kWh during transport conditions, is presented in Fig. 9, along with transport energy presented when idling. As per the substantiative literature that exists, there appears to be a moderate change in transport energy consumed during colder periods; however, in Fig. 9, there is very pronounced evidence of substantially increased energy usage during colder periods, which can be largely attributed to the use of heaters when idling. With evidence of significant efficiency improvements over time, each bus as part of an electric fleet is exposed to this issue, which becomes more acute over time. We must note that energy driven in this context indicates the total energy consumed while the vehicle was driving; that is, energy driven equals energy consumed driving less energy regenerated driving. The average energy usage is identified to be 14 kWh per hour analysed in the period before winter 2019/2020. However, at the onset of colder temperatures, increased this temperature usage to 16kWh. When idling, energy usage is approximately 0.6kWh per hour in the period before winter 2019/20; during the onset of colder conditions, this energy usage almost doubles to 1.2kWh per hour.

4.2. Weather effect on energy regenerated

Such results relating to differentials in energy consumption due to temperature differentials also manifest in a secondary effect, namely that of reduced energy regeneration. In Fig. 9, we observe the energy regeneration rate when driving as measured in kWh. From the beginning of service through to August 2019, the average energy regeneration rate was 5.3kWh. However, as temperatures begin to decrease through September, there is a pronounced period of decreased regeneration, with rates often decreasing substantially below 4.0kWh. In April 2020, there is evidence of an increased level of energy regeneration as rates increased substantially to an average of 5.6kWh per hour of driving. As stated earlier, in conditions with decreased levels of grip, such as those of increased levels of rain or decreased temperature, electric buses may experience a reduction in the energy captured during regenerative braking, whereas if slippery conditions are detected, regenerative braking will be turned off until the bus comes to a complete stop, resulting in significantly reduced fuel economy in those conditions compared to a day with dry roads at the same temperature.

4.2.1. Estimating weather effects on an electric bus route

In Table 2, we present the results of the methodological estimation and the reported effects on the speed of service. We observed that temperature had a significant effect on all analysed variables within this

Table 2
Estimated weather effects on the speed of service.

Description	Constant	Rain (mm)	Wind (kph)	Temp (°C)	Freezing	Observations	R-square
Average Speed	31.531***	0.173	0.003	0.264***	0.447	7,644	0.047
	(0.465)	(0.178)	(0.014)	(0.032)	(0.324)		
Average Speed in Service	26.315***	0.223	0.011	0.355***	0.026	7,644	0.092
	(0.410)	(0.157)	(0.012)	(0.028)	(0.285)		
Time driving	0.429***	0.009**	0.001**	−0.009***	0.029***	8,226	0.059
	(0.011)	(0.004)	(0.000)	(0.001)	(0.008)		
Time in service	0.519***	0.011**	0.001*	−0.015***	0.039***	8,226	0.096
	(0.014)	(0.005)	(0.000)	(0.001)	(0.010)		

Note: The above analysis has been conducted on anonymized data. All precautions have been taken to protect the identity of the service providers, with the above analysis being presented for testing purposes. No further information with respect to the above analysis will be made available. Other variants of methodology and data provision were utilised; however, these will only be made available within a strictly confidential report. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3
Estimated weather effects on the efficiency of charging processes.

Description	Constant	Rain (mm)	Wind (kph)	Temp (°C)	Freezing	Observations	R-square
Charge cycles	0.088***	0.000	0.000	0.001***	0.000	7,519	0.014
	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)		
SOC generated	8.808***	−0.038	0.000	0.067***	−0.040	7,519	0.014
	(0.181)	(0.061)	(0.005)	(0.013)	(0.128)		

Note: The above analysis has been conducted on anonymized data. All precautions have been taken to protect the identity of the service providers, with the above analysis being presented for testing purposes. No further information with respect to the above analysis will be made available. Other variants of methodology and data provision were utilised; however, these will only be made available within a strictly confidential report. SOC charged is the percentage of the vehicle battery that was charged. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 4
Estimated weather effects on emissions statistics.

Description	Constant	Rain (mm)	Wind (kph)	Temp (°C)	Freezing	Observations	R-square
CO_2 Net Result	46.228***	0.005	0.059**	−0.670***	0.963	7,639	0.068
	(0.860)	(0.329)	(0.025)	(0.059)	(0.600)		
NO_x net result	1.243***	0.000	0.002**	−0.018***	0.026	7,639	0.068
	(0.023)	(0.009)	(0.001)	(0.002)	(0.016)		
Particle net result	0.031***	0.000	0.000**	−0.001***	0.001	7,639	0.068
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)		

Note: The above analysis has been conducted on anonymized data. All precautions have been taken to protect the identity of the service providers, with the above analysis being presented for testing purposes. No further information with respect to the above analysis will be made available. Other variants of methodology and data provision were utilised; however, these will only be made available within a strictly confidential report. CO_2 produced is the particles produced = energy used * CO_2 emissions per kWh (default value: 0.5925 kg/kWh) * percentage of non-renewable electricity used, while CO_2 saved is based on the formula CO_2 saved = distance driven * emissions per litre (default: 2.642 kg/l) * non-electric bus consumption rate (default: 35 l/ 100 km). CO_2 net result is calculated based on company emission settings. CO_2 net result = CO_2 produced - CO_2 saved. Units: kg. NO_x net result is calculated based on company emission settings. NO_x net result = NO_x produced - NO_x saved. Units: g. The particles' net result is calculated based on company emission settings. Particles net result = particles produced – particles saved. Units: g. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

section of the estimation. Evidence suggests that increased temperature is associated with a significant increase in overall average speed and average speed in service. Such effects are also associated with evidence of reduced traffic flows and, therefore, more efficient routes. As would be expected, increased rainfall and wind are found to be associated with increased time driving and overall time in service, while colder and, indeed, freezing temperatures are found to lead to an increased risk of range anxiety due to increased time between charging periods. We further focus on the effects of temperature on the efficiency of the charging process. We identify in Table 3 that temperature is the only significant variable in this section of the analysis, where there is a significant interaction between decreased temperature and the number of required charging cycles and the SOC generated.

In Table 4, we observe the estimation results when investigating the effects of weather on emissions. We again observe the significant and pronounced effects of temperature and wind. Within this context, we observe that during a storm or during freezing conditions, the efficiency of the electric bus is significantly negatively influenced, leading to reduced efficiency across a range of tested variables. In Table 5, we observe the estimation results focused on the energy consumption of the electric bus's underestimated conditions. We identified a significant and exceptionally pronounced negative relationship between temperature and energy usage, indicating that for each degree Celsius below average, there is an increased energy usage per hour of 0.143kWh during driving conditions. In all scenarios, freezing temperatures indicate added energy usage of 0.4kWh in all tested scenarios. The wind is found to have a slight but significant influence on energy consumption for the estimations focusing on data relating to idling conditions and total energy usage.

In Table 6, we observe the estimated data based on the regeneration rates of the proposed electric buses. When analysed with weather conditions included in the analysis, we can see not only significant interactions between weather conditions and energy regeneration, however, but the effects of low-temperature conditions are also

Table 5
Estimated weather effects on energy usages.

Description	Constant	Rain (mm)	Wind (kph)	Temp (°C)	Freezing	Observations	R-square
Energy consumed when driving	12.176***	0.098	0.001	−0.143***	0.489***	7,644	0.035
	(0.229)	(0.088)	(0.007)	(0.016)	(0.159)		
Energy consumed when idling	0.905***	−0.001	0.000**	−0.120***	0.420***	7,644	0.163
	(0.019)	(0.007)	(0.000)	(0.001)	(0.013)		
Total energy used	9.850***	0.042	0.016**	−0.135***	0.450***	7,644	0.016
	(0.130)	(0.062)	(0.005)	(0.010)	(0.024)		

Note: The above analysis has been conducted on anonymized data. All precautions have been taken to protect the identity of the service providers, with the above analysis being presented for testing purposes. No further information with respect to the above analysis will be made available. Other variants of methodology and data provision were utilised; however, these will only be made available within a strictly confidential report. Consumption driving is the total energy consumption while the vehicle is driving. Units: kWh. Consumption in service is the total energy consumption while the vehicle is in service. Consumption overall is the total energy consumption while the vehicle is driving or idling. Units: kWh. Energy consumed driving is the total energy consumed while the vehicle was driving, and energy was positive. Energy idled is the total energy consumed while the vehicle was idling. Energy used is the total energy consumption while the vehicle was driving or idling or if there was any positive power or speed reading. Energy used = energy driven + energy idled. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6
Estimated weather effects on energy regeneration.

Description	Constant	Rain (mm)	Wind (kph)	Temp (°C)	Freezing	Observations	R-square
Total regeneration rate	24.672***	0.188	−0.072***	0.787***	−0.823***	7,644	0.527
	(0.337)	(0.129)	(0.010)	(0.023)	(0.235)		
Energy generation when driving	3.088***	0.065*	−0.010***	0.155***	−0.254***	7,644	0.295
	(0.089)	(0.034)	(0.003)	(0.006)	(0.062)		

Note: The above analysis has been conducted on anonymized data. All precautions have been taken to protect the identity of the service providers, with the above analysis being presented for testing purposes. No further information with respect to the above analysis will be made available. Other variants of methodology and data provision were utilised; however, these will only be made available within a strictly confidential report. The regeneration rate is the percentage of regenerated energy for a vehicle. (Energy regenerated driving/ Energy consumed)*100. Energy-regenerated driving is the total energy regenerated while the vehicle is driving. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

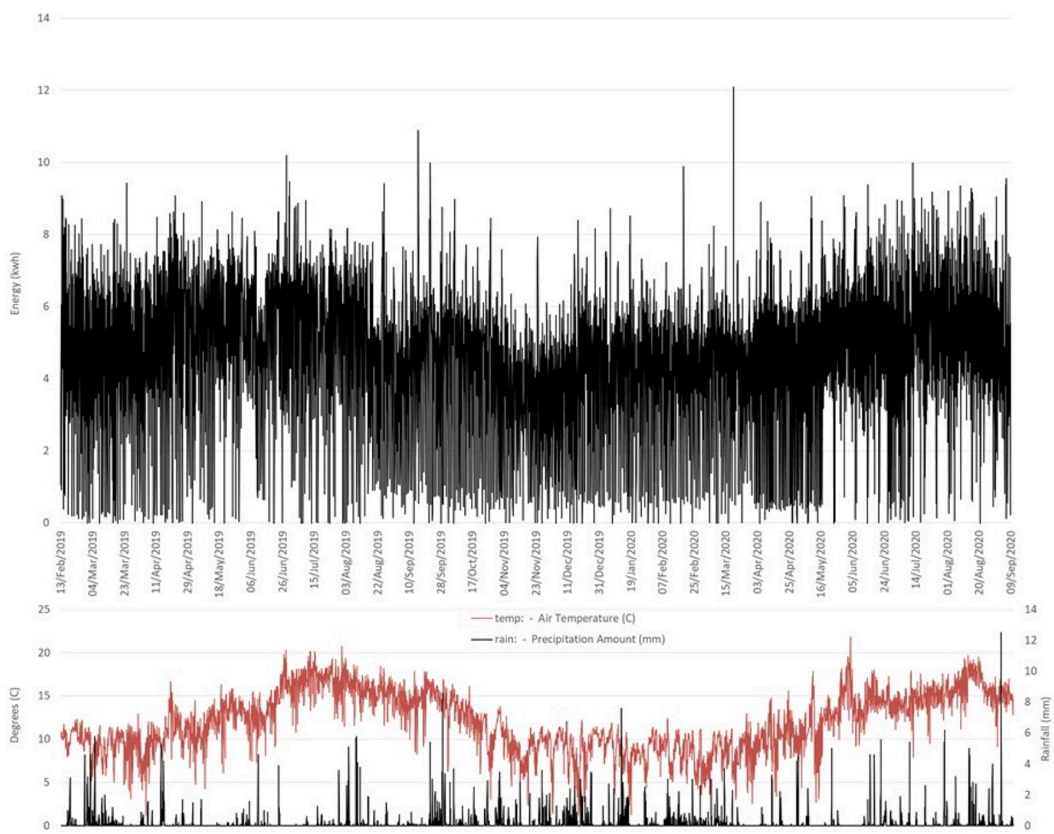

Fig. 10. Energy regenerated when driving, kWh. Note: Energy regenerated driving indicates the total energy regenerated while driving. The above temperature and rainfall data are based on an anonymized region in which the electronic bus services had operated. The data has been presented in its raw format and obtained from a reputable source with government oversight. Data relating to the bus service is anonymized.

exceptionally pronounced. This is one specific area through which technological progress will be very beneficial; however, this cannot be relied upon in the short-to-medium term period. The negative regeneration rate estimates of −0.823 and −0.254 for total regeneration rate and regeneration when driving, respectively, indicate that through all sources and the driving regeneration rate indicates that not only do the battery rates depreciate at an increased rate, but the regeneration capacity is substantially hampered.

4.3. Discussion about the external influences on the results

There are several external influences which affect the results. Firstly, the downward trend in energy consumption shown in Fig. 10 largely indicates a period of “learning” where both driver and management attempt to seek efficiency gains. It is important to note that in the search for such efficient production lie substantial cost savings, which can alleviate financial pressures from the network. However, through the provision of route-specific data and increased data observations, it would be expected that efficiency improvements can be elevated to a peak state within three to four years. The effects of “learning” are also present in the total energy usage data. In Figs. 11 and 12, we observe the presented data concerning total energy used, the total energy used when in service, and the total energy used when not in service, respectively. All measures are presented in kWh, where the energy used is the sum of energy driven plus energy idled. Throughout all presented figures, there is evidence of significant energy wastage in the early stage of the operational processes of the new company, particularly throughout the first three months. There is clear evidence that the company was trying various tactical approaches to identify what specific approach was most suitable when establishing a robust and efficient timetable. However, when removing the first three months from the sample, there is significant evidence of increased energy usage across all three measures during periods of colder temperature and elevated rainfall.

We must also note that there exist some abnormal readings in April 2020 that appear to be largely related to a combination of some issues with one bus in the fleet and a moderate route change with traffic

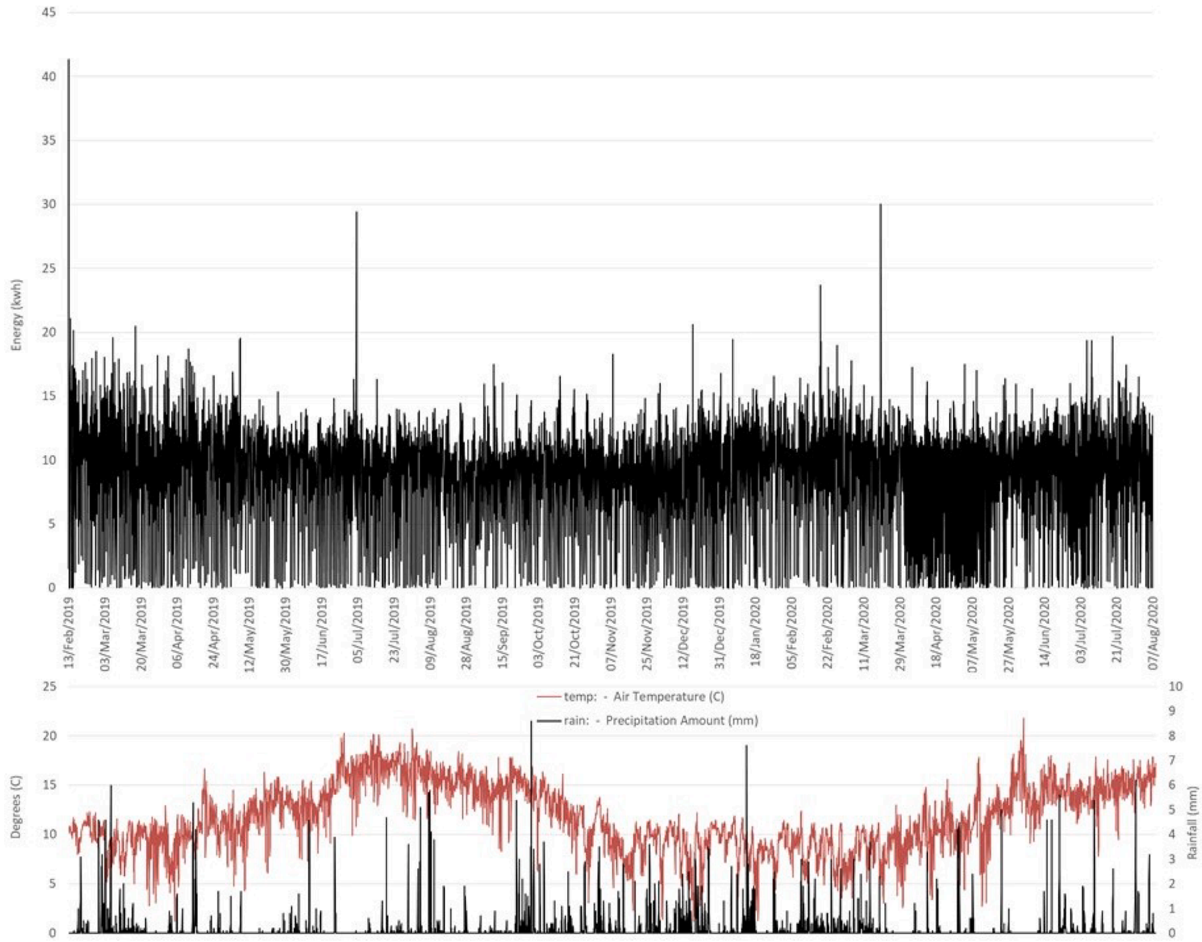

Fig. 11. Total energy used, kWh. Note: Energy used indicates the total energy consumption while the vehicle was driving or idling or if there was any positive power or speed reading. Energy used = energy driven + energy idled. The above temperature and rainfall data are based on an anonymized region in which the electronic bus services had operated. The data has been presented in its raw format and obtained from a reputable source with government oversight. Data relating to the bus service is anonymized.

i) Total energy used only when in, and not in service, kWh

ii) Total energy used only when not in service, kWh

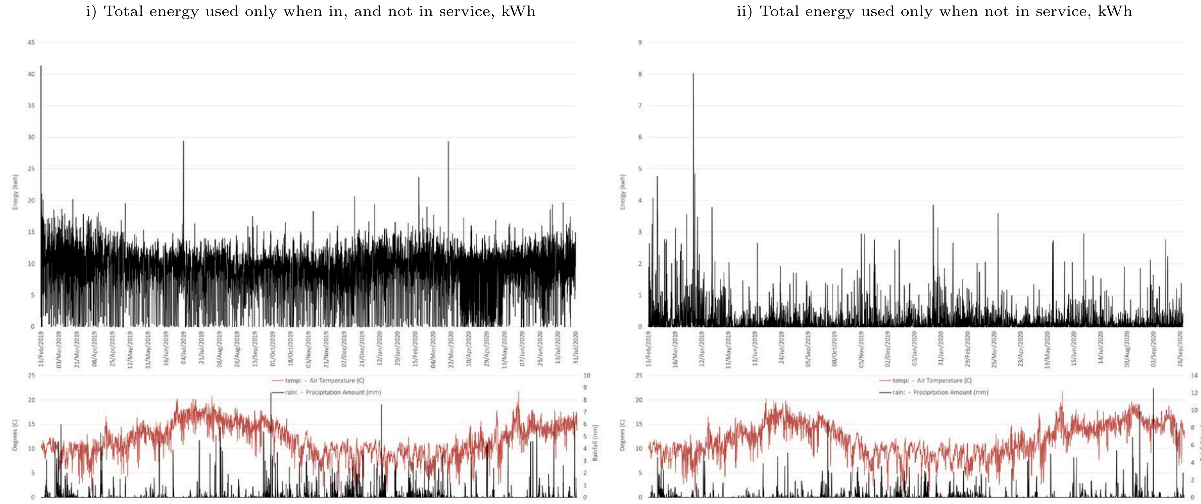

Fig. 12. Total energy used only when in, and not in service, kWh. Note: Energy used in service indicates the total energy consumption while driving or idling. Energy used = energy driven + energy idled. Energy used not in service indicates the total energy consumption while the vehicle idled for > 10 min. The above temperature and rainfall data are based on an anonymized region in which the electronic bus services had operated. The data has been presented in its raw format and obtained from a reputable source with government oversight. Data relating to the bus service is anonymized.

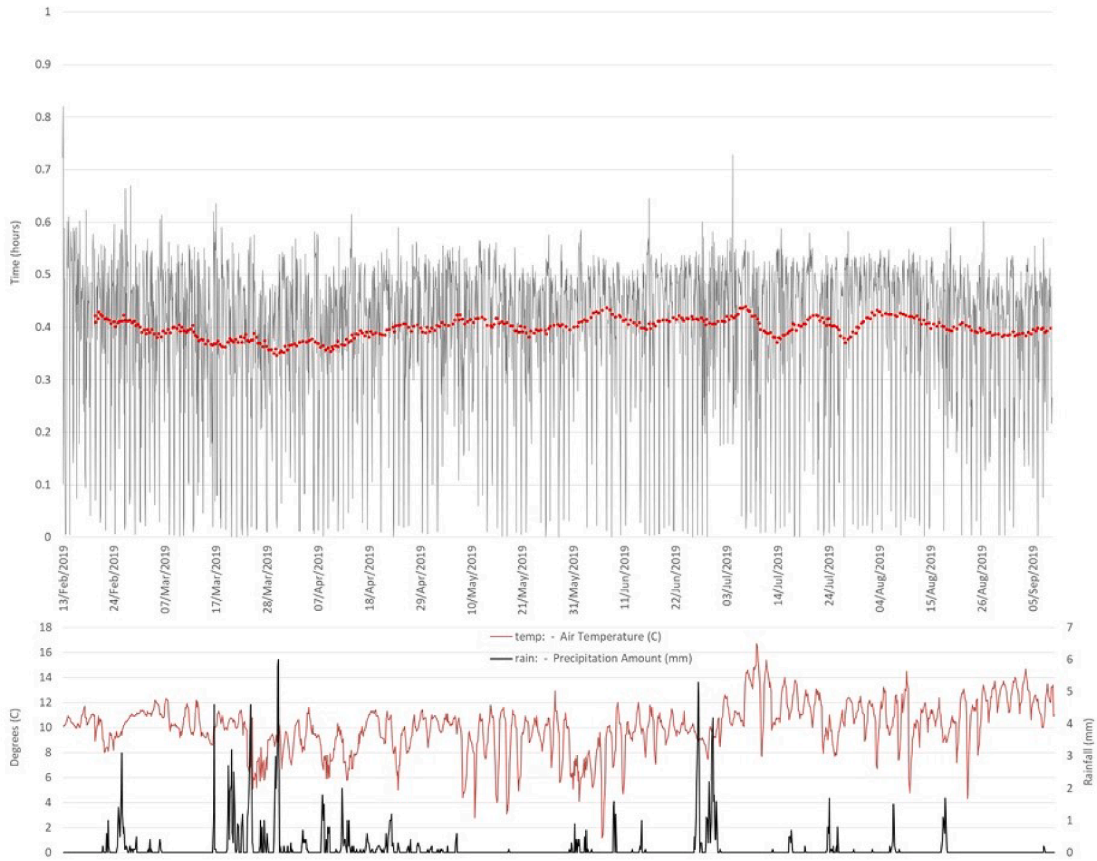

Fig. 13. Time driving, defined as when consuming energy only. Note: Time driving consuming indicates the time that the vehicle was consuming energy. The vehicle must have been driving, and the energy output must have been positive. Data relating to the bus service is anonymized. The sequenced red bullet points represent the 72-h moving average representing a three-day trend. The above temperature and rainfall data are based on an anonymized region in which the electronic bus services had operated. The data has been presented in its raw format and obtained from a reputable source with government oversight.

alterations. In Fig. 13, we observe the total time driving per hour consuming energy. We observe little in the form of significant differential apart from two periods in the summer of 2019 when various traffic alterations had taken place. Apart from this abnormal sequencing, there is moderate evidence of improved efficiency through increased minutes driving per hour over time; however, the operation has remained relatively stable since its establishment.

5. Conclusions and implications

Bus operators and policymakers need to understand the effect of inclement weather on the stability, efficiency, and feasibility of electric bus services. With this information, they can design appropriate mitigation strategies which reduce the uncertainty and risk surrounding fleet electrification. Our study uses data from a European electric bus operator and a series of standard OLS regressions to determine the impact of wind, rain, and temperature on several key performance indicators (e.g., energy consumption, total regeneration rate, service speed, and vehicle emissions). Our results suggest that a 1 °C increase in temperature is associated with a 1.17% decrease in energy consumption when driving. Additionally, freezing temperatures are associated with a further 4.02% increase in energy consumption when driving. The total regeneration rate decreases by 0.29% when wind speed increases by 1 kph, and 3.19% when the temperature decreases by 1 °C. In freezing temperatures, the total regeneration rate decreases by an additional 3.34%. Each of the aforementioned variable coefficients is significant at a 99% confidence level. These findings imply that service cost and feasibility depend on weather variables. Thus, it would be prudent to consider the local climate when deciding upon the number of long-range vehicles in operation or the quantity and position of fast chargers along the service route.

BEBs are part of the wider transition to a net-zero transportation system. For this to occur successfully, BEBs must be a good substitute for existing ICE vehicles. Our study finds that they are a near substitute to ICE buses except under colder temperatures found in most urban districts in Europe and North America, Asia, South-eastern Australia and the southern island of New Zealand. Given BEB performance under normal operating conditions at such temperatures, the policymakers should respond to encourage the technology as a net-zero measure. Commercial and state actors cannot operate existing service routes with BEBs as immediate substitutes. If policymakers were to put in place infrastructure, such as flash charging facilities, at bus stops, BEBs would be capable of becoming direct substitutes for existing ICE vehicles. In such conditions, this indirect government subsidy of building infrastructure to general inter-operable BEB standards would facilitate the rapid adoption of BEBs and a transition to net-zero public transport. Policymakers would need to ensure cost-recovery models were designed to facilitate the existence of competitive bus markets in certain jurisdictions, but those operating a tendering model with a white-label end-user experience could easily transition their fleets and physical infrastructure to net zero. Crucially, the policy will address the market failures generated by the present technology: the inability to provide a viable commercial service in cold weather, the inability to invest in or gain planning permission for new energy infrastructure (proprietary or non-proprietary), the ability to fulfil current service obligations with alternative BEB vehicles and the prohibitive costs of alternative non-ICE buses. All these prevent the rapid transition to net-zero buses, which is a policy priority, most especially in the EU and UK, where new ICE vehicle sales are to conclude within the next decade. Ultimately policymakers will need to take a systems approach where they align planning laws, capital investment in infrastructure, energy market (electricity) regulation, transportation law modernisation, competition policy and procurement policy to facilitate the rapid transition of current national ICE bus fleets to battery electric buses. A significant research agenda linking regulation, markets, technology (e.g., vehicles, motors, batteries, digitalisation) and mobility will need to be undertaken to ensure the viability of the battery electric bus.

We believe that future research investigating the impact of inclement weather on electric bus services should gather real-world data on key operational performance indicators (such as energy consumption and bus availability) and perform a series of OLS regressions to provide interpretable results for bus operators and policymakers. Furthermore, we suggest that it would be valuable to use a dataset which excludes route alterations and the period of learning observed during the first several months of a new bus service's operation.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.cstp.2023.100971.

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