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Analyzing Energy Efficiency and Battery Supervision in Electric Bus Integration for Improved Urban Transport Sustainability

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Abstract: Addressing the critical challenge of reducing local emissions through the electrification of urban public transport, this research specifically focuses on integrating electric buses. The primary objectives are to evaluate energy efficiency and ensure battery cell supervision. Introducing electric buses plays a significant role in reducing emissions, contributing to more sustainable urban transport systems. However, this transition introduces a set of new challenges, including the complexities of electric charging logistics, the establishment of new consumption standards, and the intricate relationships between distance traveled, ambient temperature, passenger load, and battery health. Methodologically, this study collects and examines factors impacting energy consumption, including external temperatures, bus conditions, road conditions, and driver behavior. By analyzing these variables, a baseline for actual consumption can be established, allowing for the calculation of an energy balance to identify energy inefficiencies. This enables the optimization of route planning, the strategic selection of stops, and the efficient scheduling of charging times, along with ensuring the proper scaling of the bus battery system. This study found that energy consumption peaked at 116.73 kWh/100 km in the lowest temperature range of −5 °C to 0 °C. Consumption decreased significantly with rising temperatures, dropping by 25 kWh between 5 °C and 10 °C and by an additional 10 kWh between 10 °C and 15 °C. Beyond 20 °C, variations were more influenced by route and driving style than by temperature. Route and driver variability significantly influenced energy consumption, with up to threefold differences across routes due to factors such as road type and traffic volume. Additionally, there was a 31.85% difference between the most and least efficient drivers, highlighting the critical impact of driving style. Furthermore, this study explores the assessment of battery systems through cell-level diagnostics to detect potential faults. Considering that buses are equipped with significantly more batteries than typical electric vehicles, detecting and localizing faults at the cell level is crucial to avoid the substantial costs and environmental impact associated with replacing large battery systems. Utilizing the results of this research and the applied examination methods, it is possible to enhance energy efficiency and extend battery life, thereby contributing to the development of more sustainable and cost-effective urban transport solutions.

Keywords: electric buses; energy efficiency; energy loss reduction; battery system testing

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1. Introduction

In recent decades, the problem of global warming has received increasing attention, leading to a growing demand from society and lawmakers to reduce emissions. The functioning of economic sectors and the close link between transport and the economy significantly impact CO_2 emissions in individual countries. In China, it has been shown that the demands of other economic sectors cause the majority of CO_2 emissions from the transport sector [1]. In the European Union, transport is responsible for nearly 30% of CO_2 emissions, of which road transport accounts for 95% [2]; moreover, CO_2 emissions from transport increased by 26.5% in 2019 compared to 1990 [3]. This shows that further measures and improvements are needed to meet climate protection targets. Technological vehicle advances have reduced CO_2 emissions from passenger cars in Western Europe, but economic activity and motorization remain proportional to emissions [4]. The spread of alternative fuels and clean vehicle technologies can play a major role in reducing carbon emissions [5]. However, the uptake of electric vehicles (EVs) does not necessarily reduce a country's CO_2 emissions; for example, China has not been able to reduce its carbon dioxide emissions at the national level because its electricity is 80% coal-fired. As the uptake of EVs increases, so does the need to improve methods of generating electricity [6]. Urbanization can increase energy consumption and CO_2 emissions from transport, especially in less developed areas where transport infrastructure has not yet been optimized [7]. The development and use of public transport can greatly reduce carbon emissions from the transport sector [8].

Electric public transportation, such as battery electric buses (BEB) and rail vehicles, is helping increase energy efficiency and environmentally friendly transport solutions. To improve their impact, it is necessary to understand the factors that affect them [9]. Traditionally, trains have been an efficient mode of transport for large volumes of passengers and freight, especially over longer distances [10,11]. They also have the advantage of using green energy indirectly from the grid, reducing dependence on fossil fuels and carbon emissions. Relevant issues for the energy consumption of rail vehicles include track conditions, weather, and the role of regenerative braking [12].

The expansion of BEB is particularly noticeable in urban transport systems, where reducing noise and air pollution is a priority. The absence of exhaust emissions directly improves urban air quality and can have additional benefits when electricity is generated from sustainable sources [13]. Furthermore, measurements have shown that BEBs have better noise and vibration emissions for the environment and passengers than diesel buses [14].

Batteries in EVs provide the energy required for movement. Battery technology in EVs can be of different types and sizes, and their environmental impact may differ over their life cycle. Using seven different BEBs, Ager-Wick Ellingsen et al. analyzed three different lithium-ion battery technologies (LTO, LFP, and NMC) of various sizes. The analysis shows that LTO batteries are advantageous for smaller battery packs and frequent fast charging. The NMC battery is favorable for vehicles with higher capacity and range [15]. For hybrid battery systems, LTO and LFP cells are recommended [16].

BEBs are typically purchased by companies for use over decades, so life-cycle costs are a key consideration when purchasing them. Using cost simulation, it has been found that, depending on the charging modes, a BEB can be from 7% to 35% more expensive over its lifetime compared to a diesel bus [17]. According to research by Kim et al., by 2030, the total cost of ownership of electric buses will be 23% lower than that of diesel buses, and this is worth taking into account for current purchases [18]. Another important aspect is monitoring the condition of the buses in service in terms of periodic maintenance and vehicle replacement. The most costly component of the system, the battery, is measured by the State of Health (SoH) value. Mingant et al. described and tested a SoH prediction method using the modules' real current and voltage values. The method is based on data from aging tests of two test modules over seven months [19]. In another approach, a model tree was created to analyze the BEB power consumption. Then, the parameters with the highest impact on consumption were ranked using Random Forest, XGBoost, and LightGBM algorithms. These are ambient temperature, average speed, average accelerator pedal position, and traffic impact congestion index [20].

Consumption is a significant expense for fleet owners and is often used as a basis for comparing the performance of individual drivers, even in terms of salary. Before analyzing drivers, the parameters that influence consumption must be grouped in terms of which factors are driver-dependent and which are independent of the driver [21]. Over four years, the parameters that influence the consumption of EVs were studied in the city of Birmingham, United Kingdom (UK), based on more than a thousand measurements. The analysis classified driver behavior into three classes: aggressive, average, and cautious.

The aggressive driving style resulted in a 7% increase in energy consumption compared to the average and a 16% increase compared to the careful driving style [22]. A method to reduce the energy consumption of buses is the implementation of eco-driving courses for professional drivers. However, the courses lose their effectiveness after approximately six months, as drivers return to their previous habits [23]. At this point, they are required to update their knowledge, or it is possible to use driver assistance programs that can provide permanent on-screen advice on the correct driving style, for example, the use of pedals and regenerative braking systems [24,25]. Furthermore, a driver monitoring system can be used to improve BEB's traffic safety [26].

To achieve safe driving, BEB drivers and operators must also know the State of Charge (SoC) of batteries to plan their travel distance continuously [27,28]. The main inputs to the model estimating the expected SoC value are the historical consumption of the considered route, the preferred speed, and the maximum acceleration and deceleration values. The model could predict the evolution of the SoC with an error of less than 2% [29].

The charging of the BEB and its associated infrastructure should also be investigated as a potential environmental pollutant [30,31]. Nazarenus et al. analyzed the impact of different charging methods on the size of BEB batteries and the load on the electricity grid. Four charging methods were investigated: overnight charging, end-line charging, occasionally fast charging, and wireless charging. Their results show that overnight charging requires the highest battery capacity, while wireless charging significantly reduces battery size and weight [32].

The early detection of malfunctioning batteries is important for electric vehicles, and there are several ways to detect them [33]. In particular, new methods need to be identified in the area of the powertrain [34,35]. In the case of BEB, Fang et al. conducted a fault diagnosis to determine the cell voltage inconsistency of battery packs in electric vehicles. The developed prediction method is based on measurement data from 20 buses [36]. Another method for detecting faulty cells was developed based on a diagnostic approach using normalized voltage values. The process can detect small deviations and thus provides a faster fault indication compared to the BMS system [37].

Research on the consumption of electric buses and the factors influencing it is currently a popular research area, with several publications available [20,38,39]. Concerning the effects of temperature, studies have shown that deviations from the optimal temperature range (between −27 °C and 35 °C) can increase energy consumption by up to 47% [40], while measurements in Hungary have shown an increase of 50–70% between −12 °C and 4 °C [41]. Research on electric buses in Espoo and Helsinki observed a 24% higher consumption on urban road sections, with no significant changes noted in the role of regenerative braking [38]. In winter, heating and other auxiliary loads can account for up to 50–70% of total energy consumption, with significant implications for battery size and energy management [42]. Measurements in Qatar showed that in 48 °C heat, energy consumption increased by 40–50%, with air conditioning accounting for 30% of the total consumption [43]. The role of air conditioning is particularly significant; it has been shown to double energy consumption at 60% capacity, comparable to driving uphill at a 2% gradient with 25 passengers [44]. Comparing winter and summer consumption, peak summer temperatures resulted in an energy consumption of 1.35 kWh/km, whereas consumption below 0 °C reached 2.1 kWh/km, reflecting the significant energy demand for heating [45].

Based on previous publications, it can be concluded that winter temperatures in Hungary are particularly important in studying the energy consumption of electric buses, as this is where the most significant variations are expected. Additionally, when analyzing routes, significant differences between various lines can be observed, and the role of regenerative braking may be substantial, in contrast to earlier findings. This research aims to comprehensively investigate these factors across a wider range of temperatures and conditions specific to Hungary. This study's novelty lies in its integrated analysis of the combined effects of temperature, route, cooling, and heating on the energy consumption of electric buses, building on but extending previous research. The tools, routes, and calculation methods are presented in the second section. In the third section, the different parameters are analyzed separately. The fourth section summarizes the results obtained under the different aspect parameters.

2. Materials and Methods

The measurements were carried out in Győr, Hungary, in 2024 on 13 BYD K9UD e-buses in new condition. The vehicles have their charging point at the public transport operator in Győr. The buses arrive at the site after operating hours, start charging, and begin every journey at 100% capacity. For winter operations, pre-heating can be activated so the vehicle can enter the road with a pre-heated passenger compartment. This has the particular advantage that the additional energy needed is supplied from the electrical grid through the charging port. In cold weather, the use of a heat pump reduces the range, so to compensate for this, an auxiliary heater is provided. When interpreting the results, it is essential to note that the consumption values are calculated based on the charge. Values were collected using the FleetLink data communication system. The disadvantage of this method is that the energy consumed while charging the bus and the charging frequency may influence the results. However, in this case, data are available for all buses participating in public transport. Direct consumption measurement is also used for more accurate analyses, but the number of samples is significantly lower. To perform the measurements, it was necessary to access the internal diagnostics of the bus using a measurement system.

Figure 1 shows the main elements needed to read the data. In part A of the figure, the tool made by GODIAG Auto Tools (Shenzhen, China) is shown. The GODIAG GT100 is an ECU programming and testing tool that allows the programming and testing of ECU modules on different vehicles. The diagnostic connector of the bus is shown in part B. Part C shows the ZLG USBCAN II (ZLG Zhiyuan Electronics Co., Ltd., Guangzhou, China), a USB-based CAN (Controller Area Network) interface designed to connect and communicate with various CAN networks. These were connected to the computer's USB port, where data were read using the K9 assistant BMS monitoring software (UI-160805).

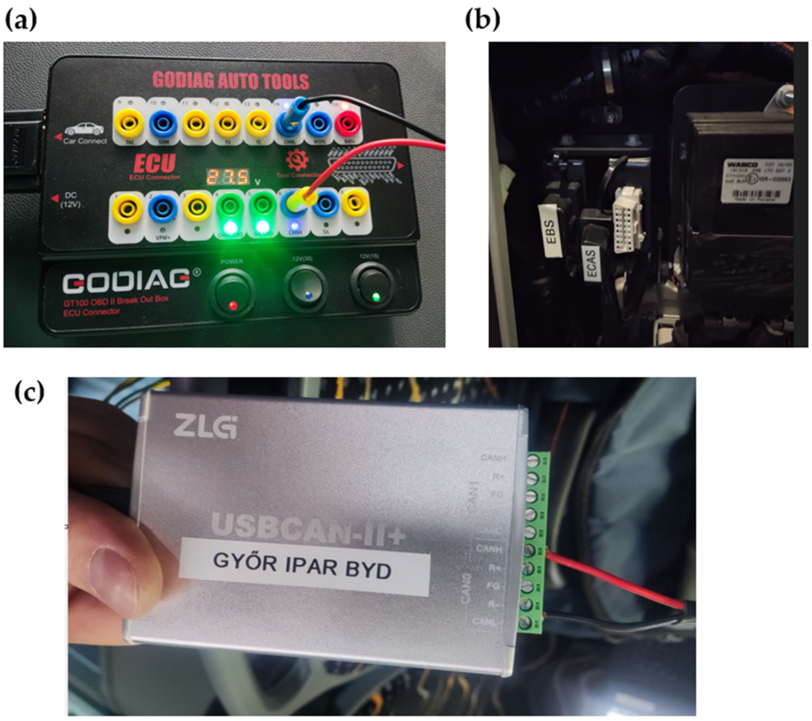

Figure 1. Diagnostic tools used to measure the electric bus (**a**) ECU programming and testing tool; (**b**) bus diagnostic connector; (**c**) USB-based CAN interface.

The tests were carried out in the city of Győr on local electric buses. In Figure 2, a map of public transport highlights more than 20 urban lines, and they are very different in terms of length and traffic. Of these lines, more than 15 were analyzed.

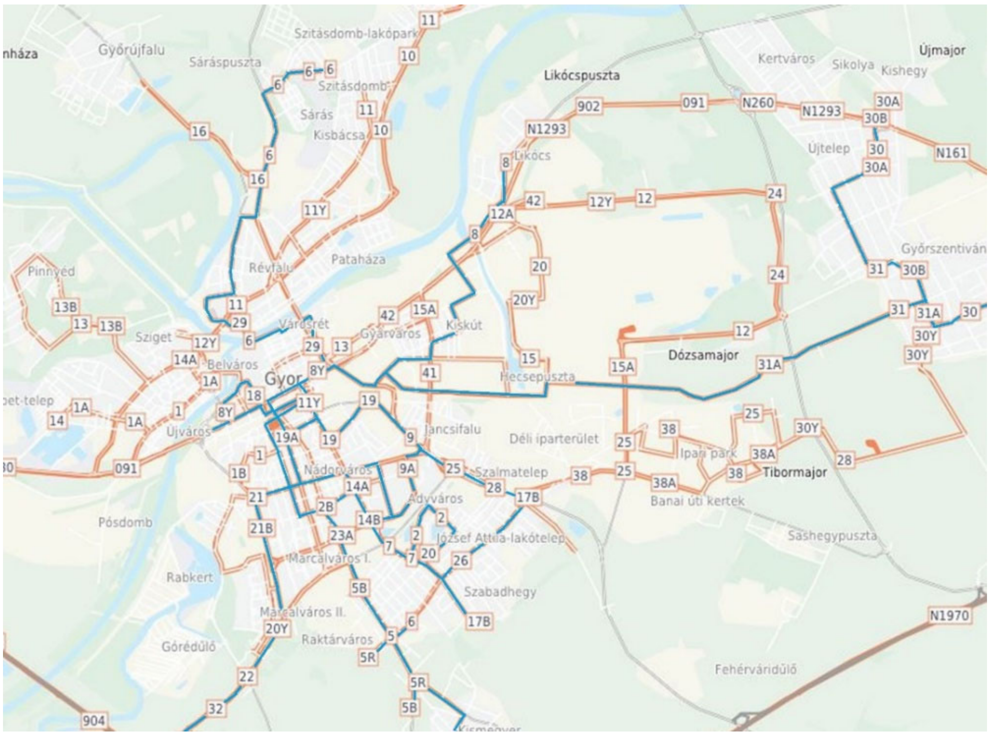

Figure 2. Bus routes in the city of Győr.

This study identifies several factors that can significantly influence the results. The first category includes environmental and external factors, such as temperature, weather conditions (e.g., rain, snow), and road conditions (e.g., slipperiness, slopes). These are followed by technical and operational factors, encompassing battery capacity and the buses' energy consumption, which may vary with changes in vehicle speed. Human influences are also crucial, manifested through driver behavior, driving style, and the number and distribution of passengers. Organizational and strategic factors, such as route planning, stop allocation, and charging strategies, can also affect outcomes and reproducibility. Lastly, financial and economic factors may arise when modifying routes and stops or using air conditioning consumption control. Each influencing factor, as well as those omitted, is addressed within the specific analysis.

The different parameters examined involve partially or entirely different computational approaches. The analysis of the consumption data of the buses in Győr was carried out according to the following:

i. Analysis of bus consumption data as a function of temperature

The temperature impact analysis was based on the fleet's average daily consumption of all-electric buses taken from the FleetLink system. The daily average temperature was standardized with the average consumption values, and a subset of these was used to produce statements with daily and monthly breakdowns. It should be emphasized that the analyses are not comprehensive for an entire year; rather, they primarily focus on assessing the impact of winter weather conditions.

ii. Analysis of the air conditioning consumption of electric buses

These measurements were performed on the ID-174 bus on the same route with a small variation in temperature and weather conditions using the measurement system shown in Figure 1. The measurements were conducted under the coldest possible conditions but were analyzed based on a limited dataset. The instantaneous current and voltage values were used and added to calculate the energy for the three modules.

$$Q_{sum} = \sum_{1=1}^{n} (U_{1,i} \cdot I_{1,i}) \cdot \Delta t + \sum_{1=1}^{n} (U_{2,i} \cdot I_{2,i}) \cdot \Delta t + \sum_{1=1}^{n} (U_{3,i} \cdot I_{3,i}) \cdot \Delta t \tag{1}$$

where $i = 1, 2, \ldots, n$ are the discrete time points, and Δt is the time interval between each measurement. The instantaneous current $\{I_{1,i}\}$, voltage values $\{U_{1,i}\}$, and modules are indicated by a number. The measurements include a time stamp so that the two days can be compared at any point in time. The current change rate was considered to determine the dynamics of the measurement.

$$\left(\frac{dI}{dt}\right)_{j,i} \approx \frac{I_{j,i+1} - I_{j,i}}{\Delta t} \tag{2}$$

where $\left(\frac{dI}{dt}\right)_{j,i}$ represents the rate of change of current for the j-th module at the i-th time point. $I_{j,i}$ and $I_{j,i+1}$ are the current values for the j-th module at the i-th and $(i+1)$-th time points, respectively. Δt is the time interval between measurements.

iii. Bus driver's impact on energy consumption

Data for analyzing bus drivers were also taken from the FleetLink system. The drivers and buses were coded with IDs determined from the local bus company's database. Daily consumption values were first assigned to buses and then to drivers. Analyses and comparisons were made on this basis. The analysis is based on different data quantities for each driver.

iv. Impact of differences between routes on the consumption of electric buses

More than 15 routes and 10 buses were examined in the route analysis. Cases with only a few values are not presented. The system shown in Figure 1 was used to record the data. Energy consumption and recharging were also calculated based on instantaneous current and voltage values. In all tests, data were recorded accurately but manually at the start and end of the line. Based on this, the data had an accuracy of approximately a few seconds per route and line. Each line was calculated separately in the evaluation, and the values were added together to determine the daily value. The measurements were conducted on different days, resulting in diverse weather conditions. Additionally, traffic conditions may have also varied.

v. Cell-level diagnostics and condition assessment of electric buses

The electric buses used were in new condition, meaning their battery systems were assumed to be in good condition. The aim of the diagnostics was to check the individual cells using a different approach than the internal calculator. The buses under study had three separate motorized systems with information from 156 cells, so a total of 468 elements could be compared. The method used was to investigate deviations from the average voltage, which has been applied in several studies on EVs [32]. The approach consists of examining the average voltage of each mode (there are 3 in total) and determining the number of deviations. For each measurement time point t, the average voltage $\overline{V}'_t$ is calculated across all 156 cells, distributed in 3 modules. The cells' indices range from 1 to 156. The determination of the average voltage is as follows:

$$\overline{V}_t = \frac{1}{156} \sum_{i=1}^{156} V_{it} \tag{3}$$

where V_{it} is the voltage of the i-th cell at time point t. Next, the average voltage value $\overline{V}'_t$ is reduced by a predetermined ΔV value (e.g., 20 mV, 50 mV)

$$\overline{V}'_t = \overline{V}_t - \Delta V \tag{4}$$

where $\overline{V}'_t$ is the reduced threshold voltage. The deviations are reassessed based on the reduced simple average. For each cell, we calculate a binary deviation indicator:

$$D_{it} = \begin{cases} 1, & ha \left| V_{it} - \overline{V}'_t \right| > 0 \\ 0, & otherwise \end{cases} \tag{5}$$

where D_{it} is a binary value that equals 1 if the cell's voltage deviates from the reduced average. Given that there are three modules, the cells are indexed from 1 to 156 without dividing into subgroups for modules. Thus, the above method was applied across all cells irrespective of module division. In summary, the method to identify weaker cells involves calculating the average voltage across all cells at each time point, reducing this average by a predetermined voltage difference, evaluating deviations based on the reduced average, and marking cells that deviate significantly. The greater and more frequent the deviation, the more likely the cell will be considered weak and critical.

3. Results and Discussion

This analysis examined the average consumption of a fleet of electric buses. The overall average for this study was 94.56 kWh of energy. From the consumption value of 0.95 kWh/km, it can be concluded that the maximum distance a bus equipped with a 275 kWh net capacity battery can travel is 290 km if its energy storage is 100% charged at start-up. However, several factors can strongly influence this average value, which will be analyzed in detail in the following sections.

First of all, the consumption of each fleet vehicle can be observed in Figure 3. The figure shows that there can be a difference of up to 10–12 kWh in average consumption between vehicles (more outliers, possibly due to the lack of measured data). This can result in a difference of up to 20% per 100 km. It is important to note that this average value is calculated from September 2023 onwards and does not only apply to the period covered in this study. To better understand the differences, the following aspects are analyzed more deeply (see Figure 4): temperature effect, heating and air conditioning, differences between bus drivers (driving style), and different bus routes. The battery modules were also analyzed for condition assessment.

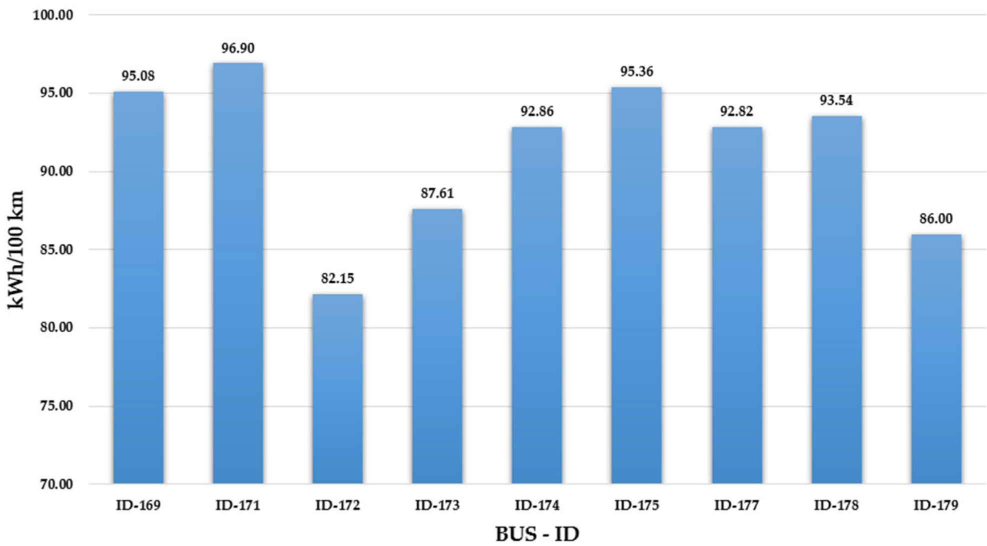

Figure 3. Consumption of BYD K9UD buses based on energy consumption measured from the charging station (kWh/100 km).

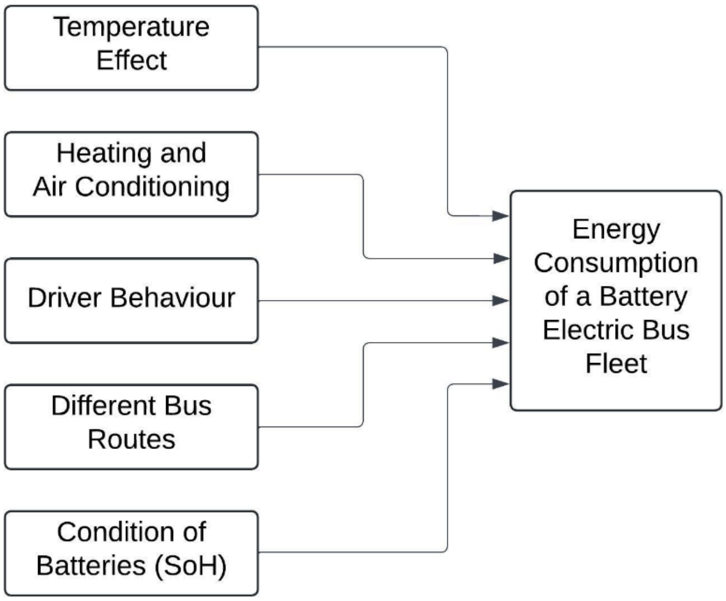

Figure 4. Parameters influencing the consumption of a fleet of electric buses.

3.1. Analysis of Bus Consumption Data as a Function of Temperature

Due to temperature changes, there can be significant differences in consumption values. The time period analyzed was January to April 2024. These values may differ for other cities and buses but are similar in magnitude. Figure 5 shows the weather in Győr for the period under study.

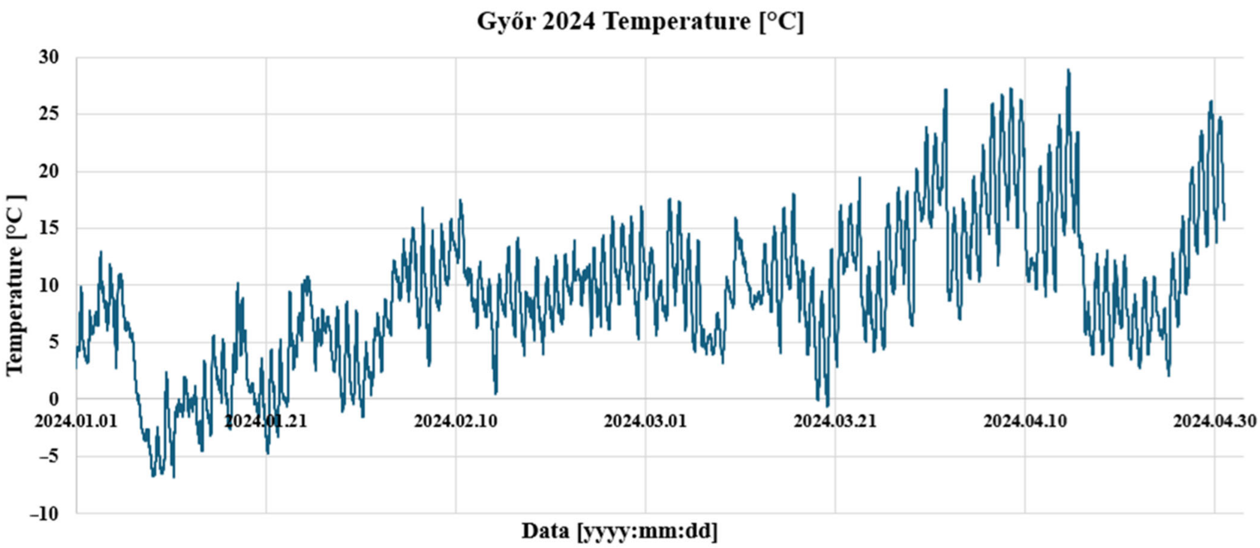

Figure 5. Weather data for Győr between January and April 2024.

The whole-day data with 10 min sampling from the measuring station at Széchenyi István University, Győr, Hungary (StationNumber: 23,714) can be seen in Figure 5. There were no sustained negative degrees during the period; colder weather was observed in mid-January and mid-April. During the other periods, the temperature was relatively stable at 5–15 °C. The relationship between average daily consumption and temperature is examined below in Figure 6 for the month of January.

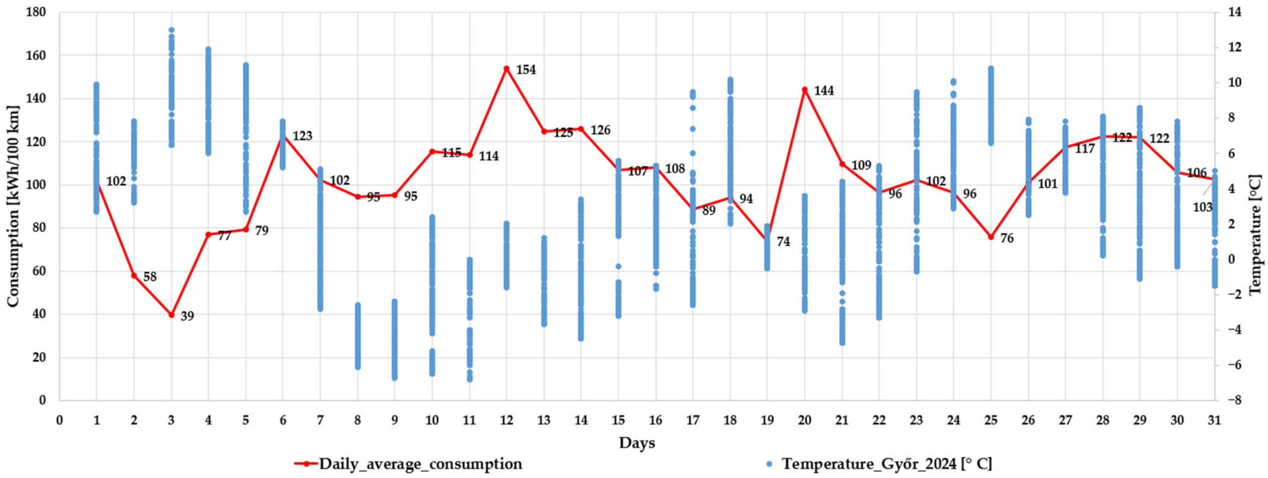

Figure 6. Correlation between January consumption and temperature.

The analysis shows daily temperature data in blue dots, sampled over 10 min. The red line shows the change in average consumption. It is important to note that the daily average electric bus consumption was used. It can be observed that the coldest period was between January 8 and 11 and that consumption also increased. In the analysis, there were so many delays that the energy consumed was calculated based on the charges carried out at the end of each day's rounds. In general, there are two daily charging data sets, one at around 13:00 and the evening charging, which was delayed to after 0:00 in several cases. It can be seen that consumption decreases on the warmer days. It can also be observed that the coldest day does not necessarily cause the highest consumption; it is probably a more complex process, partly influenced by the temperature change. However, the trend is that colder outdoor temperatures, on average, cause higher consumption.

Figure 7 shows the consumption data for the different buses in January, and the consumption varied between 80 kWh and 102 kWh. The values shown are for 100 km and are calculated in each case based on the energy used during the charge. It is important to note that the ten buses presented did not always run on the same route and on the same days. Therefore, a bus that uses a route with a higher energy consumption during a period and in cold weather is expected to use more energy. The most significant difference of the month, which is 20%, is worth noting.

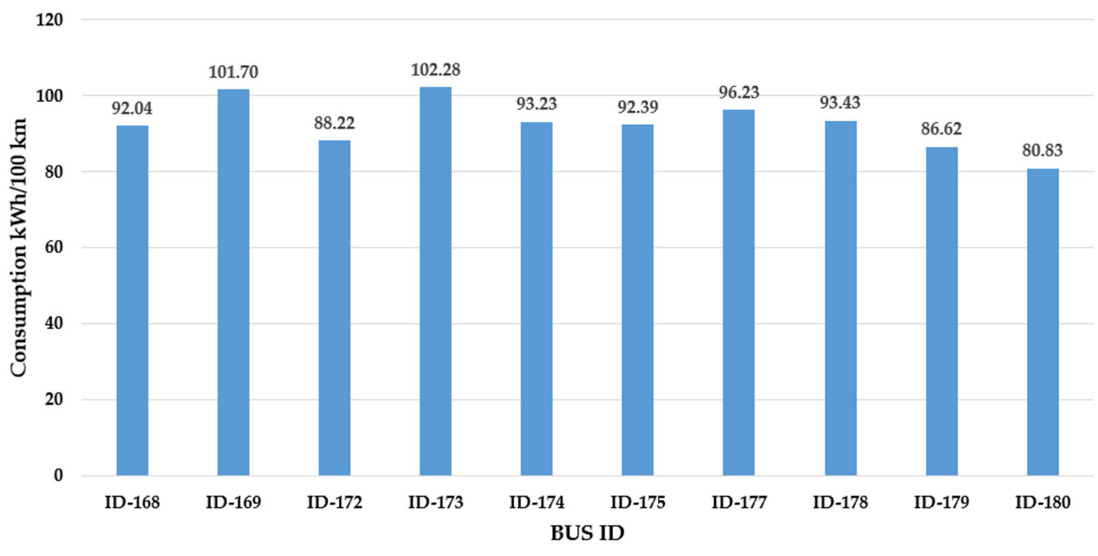

Figure 7. Average consumption of electric buses in January.

The month of February is shown in green in Figure 8, where the first few days were colder, resulting in higher fleet consumption, while the other days showed a relatively similar temperature with a smaller variation. The average values for March (blue line) followed the trend more closely because extreme temperatures (i.e., below 0 °C) no longer occurred. The average consumption in April (black line) was stable, with higher temperatures. This suggests that higher daily temperatures lead to more predictable fleet consumption. Table 1 shows the aggregated results for the temperature intervals.

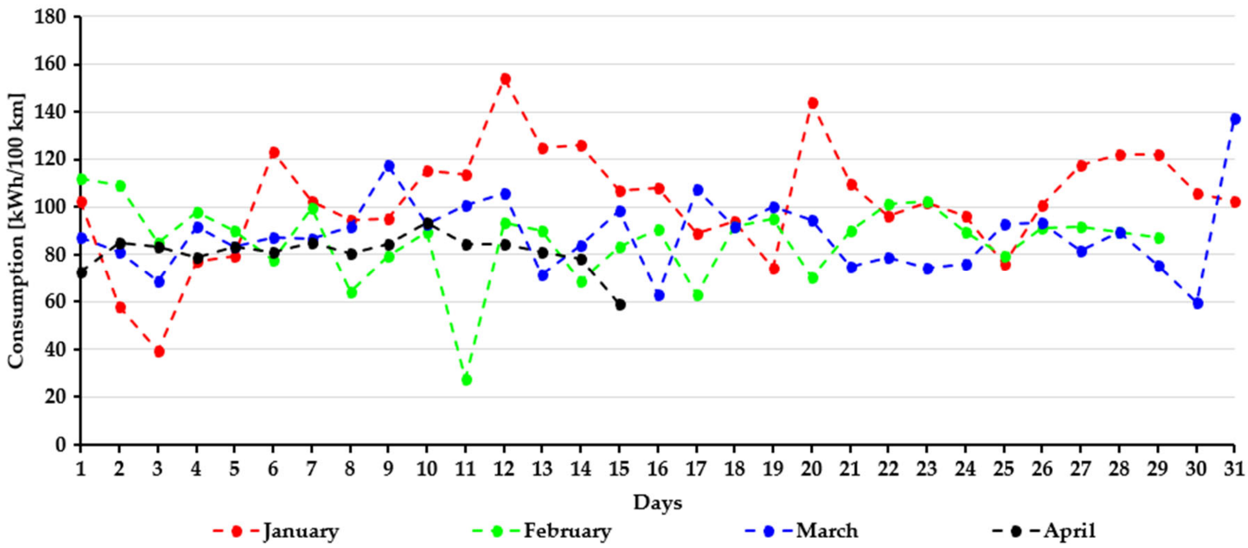

Figure 8. Average fleet consumption at daily resolution for different months.

Table 1. Average consumption aggregated by temperature.

Temperature	Average Consumption of the Fleet [kWh/100 km]
−5 °C to 0 °C	116.73
0 °C to 5 °C	106.17
5 °C and 10 °C	90.33
10 °C and 15 °C	80.90
15 °C and 20 °C	70.05
20 °C and 25 °C	78.86

Based on the results, a trend was established based on consumption per 100 km traveled. This suggests that temperatures below 0 °C are the most critical, closely followed by consumption data at and around 0 °C. The 25 kWh lower consumption between 5 °C and 10 °C is a significant value. Differences are also observed between 10 °C and 15 °C, and in the 15 °C to 20 °C range, approximately 10 kWh less is observed. These differences are probably more influenced by the route and driving style than by temperature. It is important to note that the value between 20 °C and 25 °C in the last row of the table is based on relatively small datasets. Therefore, this value is likely to vary in a positive direction. In summary, electric buses use more energy in cold weather (based on Table 1). However, several factors may contribute to the significant increase in the consumption of electric vehicles in winter. These factors include the following: Battery efficiency is significantly reduced at low temperatures; also, in cold weather, batteries need to use more energy for heating (in the absence of other heating) to reach their optimum operating temperature; during winter, heating is often necessary for driver and passenger comfort, increasing energy demand. It can also be noticed that consumption varies more during winter driving. There are several reasons for this, e.g., the extent to which the heating system is used (window heating, cabin heating) and whether the battery or bus is hot or cold at start-up. With an average consumption of 116.73 kWh, a maximum range of 230–240 km can be predicted for a battery with a net capacity of 275 kWh, starting from 100% SoC (State of Charge).

3.2. Analysis of Air Conditioning Consumption of Electric Buses

The calculations were carried out on the basis of Section 2: Analysis of the air conditioning consumption of electric buses. To understand air conditioning use and the factors that influence it and to assess its consumption, a two-day measurement was carried out in January during the coldest days. The test was carried out on the same bus, driver, and route, with minor variations in temperature and weather conditions. The results are comparable without significant influence of the above-mentioned factors but cannot be extrapolated to the whole fleet; however, they can be used for estimation. In both cases, measurement and the recording of data started at the depot. In the first case, the air conditioning was used normally; in the second case, it was switched off when the bus stopped for the driver's rest period. In addition, on the second day, during the stops (rest period), the bus was disconnected from the power supply; therefore, data recording also stopped. Table 2 summarizes the results.

Table 2. Analysis of the use of air conditioning in electric buses.

Data/Measurement Day	15 January 2024	16 January 2024
Time [s]	14,366	14,942
dI/dt [AVR]	14.07	11.39
Regenerative Energy [kWh]	−49.01	−40.86
Consumption_Energy [kWh]	140.20	125.80
Energy [kwh]	91.19	84.95
Energy_sum [kwh]	97.53	88.41

The first day showed regular air conditioning use (01.15—column); on the second day, the bus was stopped for rest periods/the driver's break period, and the power was switched off during the rest periods. In the comparisons, the data interruptions in these cases have been merged. The total difference between the two measurements was 6.24 kWh, a difference of 6.84%. It is important to note that in both cases, the bus's air conditioning was operating to heat the passenger cabin while driving. Furthermore, these values do not include consumption during the rest period. It can be concluded that by switching off the air conditioning, savings of approximately 7% were achieved. The additional energy associated with the higher energy demand during the heating-up period was also calculated. The total daily consumption with rest periods is shown in the seventh row. The difference is 9.11 kWh, representing savings of 9.34% when the bus air conditioning was switched off during the breaks. Although the additional difference of 2.87 kWh (difference during rest) is measurable and above the margin of error, further measurements would be needed to determine the exact amount. The advantage of continuous air conditioning (first day) is that the interior temperature of the bus was much higher and more comfortable for the passengers. In the other case (second day), a long warm-up period was needed during major stops.

3.3. Bus Drivers' Impact on Energy Consumption

In this section, the role of bus drivers in terms of energy use is examined. It is important to note that the consumption is based on charging in this case as well. Initially, nine buses were analyzed, focusing on the difference between the permanent and substitute drivers (Table 3).

Table 3. Average consumption of different electric buses of the same type.

BUS—ID	ID-168	ID-169	ID-172	ID-173	ID-174	ID-175	ID-177	ID-178	ID-180
AVR_ FLEET [kWh/100 km]	87.80	87.80	87.80	87.80	87.80	87.80	87.80	87.80	87.80
AVR_BUS [kWh/100 km]	94.23	102.93	88.28	99.20	102.46	104.77	102.14	103.74	100.38
AVR_DIFF_DRV [kWh/100 km]	94.43	97.30	87.65	104.55	101.00	97.04	100.47	101.94	100.66
AVR_BUS_DRV [kWh/100 km]	94.53	91.73	94.90	98.13	105.15	108.30	99.21	102.55	100.85

The first column of the table shows the different consumption values: AVR_ FLEET is the average consumption for the whole fleet; AVR_BUS is the average value based on all available data for the bus (January to April); AVR_DIFF_DRV is the average consumption based on substitute drivers; AVR_BUS_DRV is the average of the two drivers who drive the bus the most. The absolute difference between substitute and permanent bus drivers was 4.22%. The results suggest that this is the extent to which the bus is driven by a permanent or a substitute driver.

The first column of Table 4 shows the consumption values of the test, where Consumption [kWh/100 km] is the average consumption of the driver. FLEET [kWh/100 km] is the deviation from fleet consumption, and the fourth row (%) shows the same expressed in a percentage. The deviation in the fifth and sixth rows is based on the average bus consumption. The seventh and eighth rows show the results for substitute drivers. The columns in the table show the ID-coded numbers of the drivers in which each ID represents a new driver. The results show that permanent drivers did not always perform better on their own buses (negative value for lower consumption) than their substitute colleagues. Thus, driving style has more of an influence on the results than driving the same bus. As a final analysis, the average consumption of 18 drivers was observed, as shown in Figure 9.

Table 4. Average consumption of different drivers by electric bus.

Driver—ID	ID-76	ID-160	ID-149	ID-155	ID-35	ID-138	ID-105	ID-112	ID-13	ID-170
Consumption [kWh/100 km]	88.88	100.17	83.28	100.17	89.63	100.17	96.08	100.17	110.14	100.17
FLEET [kWh/100 km]	1.08	12.37	−4.53	12.37	1.83	12.37	8.28	12.37	22.33	12.37
%	1.23	14.09	−5.16	14.09	2.08	14.09	9.42	14.09	25.43	14.09
BUS [kWh/100 km]	−5.34	5.95	−19.65	−2.76	1.35	11.90	−3.12	0.97	7.67	−2.29
%	−5.67	6.31	−19.09	−2.68	1.53	13.48	−3.15	0.98	7.49	−2.23
DIFF_DRV [kWh/100 km]	−5.55	5.74	−14.03	2.87	1.98	12.53	−8.47	−4.37	9.14	−0.83
%	−5.87	6.08	−14.42	2.95	2.26	14.29	−8.10	−4.18	9.05	−0.82

In Figure 9, the horizontal axis shows the ID values of the different drivers, and the vertical axis shows the average consumption. This indicates that there can be significant differences between drivers. The difference between the best and the worst value was 31.85%. The average consumption was 101.33 kWh/100 km. The absolute value of the deviation was 7.21%, which shows that a deviation in both positive and negative directions is to be expected.

3.4. Impact of Differences between Routes on Consumption of Electric Buses

The following important aspect of the analysis is determining the consumption reached between each route. Figure 10 highlights the average consumption values of 12 different daily route plans.

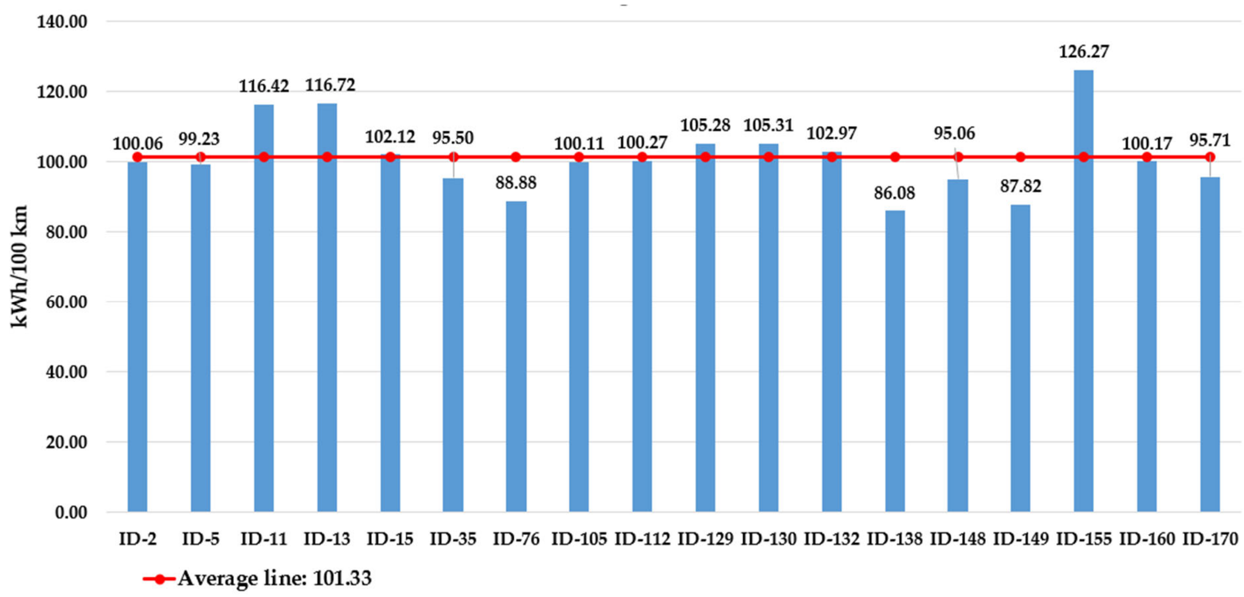

Figure 9. Average consumption of different drivers in January and April.

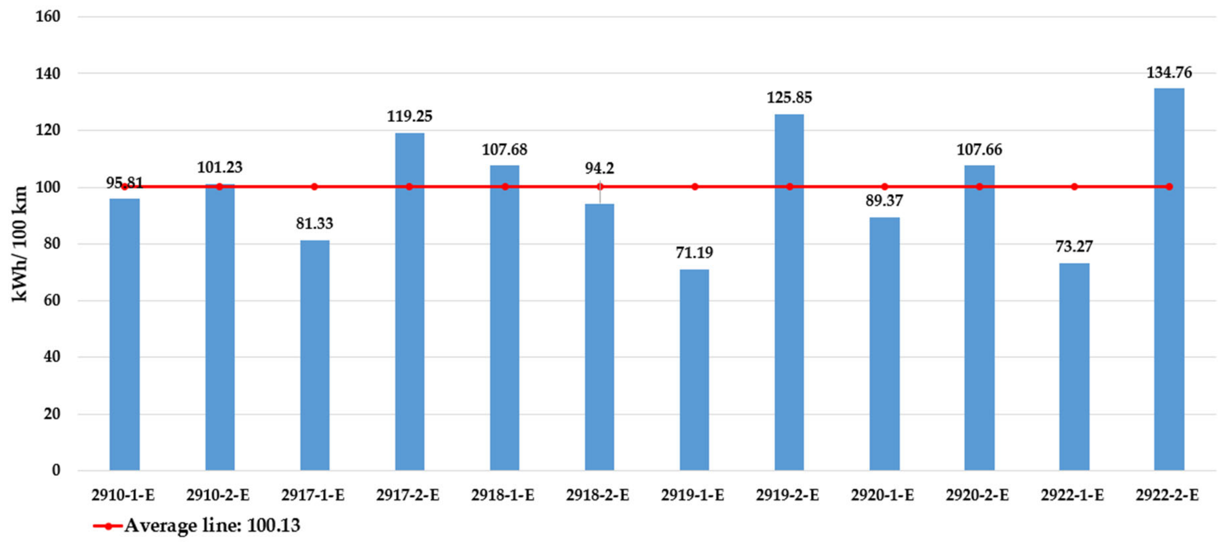

Figure 10. Average consumption for different daily routes.

Figure 10 shows how the average consumption of the different routes changed. The various names represent different bus routes with different lengths (km). It is important to note that these are daily routes, which are made up of several types of bus lines. The distances have been pro-rated in the analysis to purely include differences between routes. The average value was 100.13 kWh/100 km. The most significant difference was found to be 47.17 kWh/100 km. The absolute value of the differences between routes was 15.92%. This value may vary when further routes are analyzed, so the results should be interpreted as a guideline, but it can be observed that specific daily routes taken can greatly impact consumption. The next step was narrowing each route further to the lane level. The measurements are summarized and presented in kWh/km for ease of reference. Route direction and length were also taken into account in the analysis. Route distances are based on official data from the bus company. The results are summarized in Table 5.

In the first column of the table is a line name, with T indicating one direction and F the other. The results show that 30–40% is the most typical value. In most cases, these differences are not influenced by the weather but rather by traffic and regenerative energy. Bus routes 22 and 30 also include regional main road segments. These segments have a smoother flow and driver skill has a lower impact on consumption; therefore, there is less variation between the minimum and maximum values.

Table 5. Average consumption of buses in Győr by different lines.

Line	Distance [km]	MIN [kWh/km]	MAX [kWh/km]	AVR [kWh/km]	Deviation [%]
2-T	4.4	0.71	1.31	1.00	45.83
2-F	5.9	0.70	1.39	1.03	49.57
5-T	5.9	0.46	1.11	0.79	58.46
5-F	5.8	0.70	0.95	0.88	26.23
6-T	12.9	0.67	1.08	0.90	37.58
6-F	13.6	0.74	1.22	0.92	39.14
7	10.4	0.37	0.92	0.64	59.62
8-T	6.5	0.83	1.02	0.92	18.14
8-F	6.1	0.78	1.34	0.93	41.32
8Y-T	6.6	0.76	0.90	0.84	15.15
8Y-F	7.1	0.69	1.02	0.84	31.89
9	11.4	0.66	1.05	0.90	37.30
19	10.6	0.82	0.92	0.87	10.33
22B-T	11.7	0.72	0.90	0.81	20.11
22B-F	13.1	0.94	1.06	1.00	11.22
30-T	12.7	0.76	0.85	0.80	11.05
30-F	12.3	0.63	0.95	0.79	33.54

Table 6 shows the length and average consumption of the route, when the line directions are combined. From these values, it can be concluded that the energy demand of the different lines is very different. This can be influenced by several factors, including the type, condition, and composition of the road (roundabouts, traffic lights, and junctions)—as well as the number of passengers and the volume of traffic on the route. No correlation between the length of the route and the average energy demand could be established. The consumption of longer-distance trips could not be linked to higher unit energy consumption.

Table 6. Average consumption of buses in Győr by different lines (aggregated).

Line	Distance [km]	Average Consumption [kWh/km]
2	10.3	1.02
5	11.7	0.84
6	26.5	0.91
7	10.4	0.64
8	12.6	0.93
8Y	13.7	0.84
9	11.4	0.90
19	10.6	0.87
22B	24.8	0.91
30	29	0.80

3.5. Cell-Level Diagnostics and Condition Assessment of Electric Buses

The calculations were carried out based on Section 2: Cell-level diagnostics and condition assessment of electric buses. The divergence between modules and cells was analyzed to assess the state of the battery. A total of five tests were performed on two different buses. During each test, the battery system was monitored on a route. Two routes were analyzed in the first case and three in the second case. It is important to note that the system has three separate battery packs, which could be used to monitor 156 cells. During the backup, the three systems are saved in individual files; therefore, their results are processed separately, but the data are synchronized to make comparisons. Based on the available data, the batteries can have the following voltage ranges (based on unofficial information): Nominal voltage: 3.2 V; Maximum voltage: 3.65 V; Minimum voltage level: 2.5 V. In the first case, the bus was tested in winter weather. Figure 11 shows the results from the first measurement.

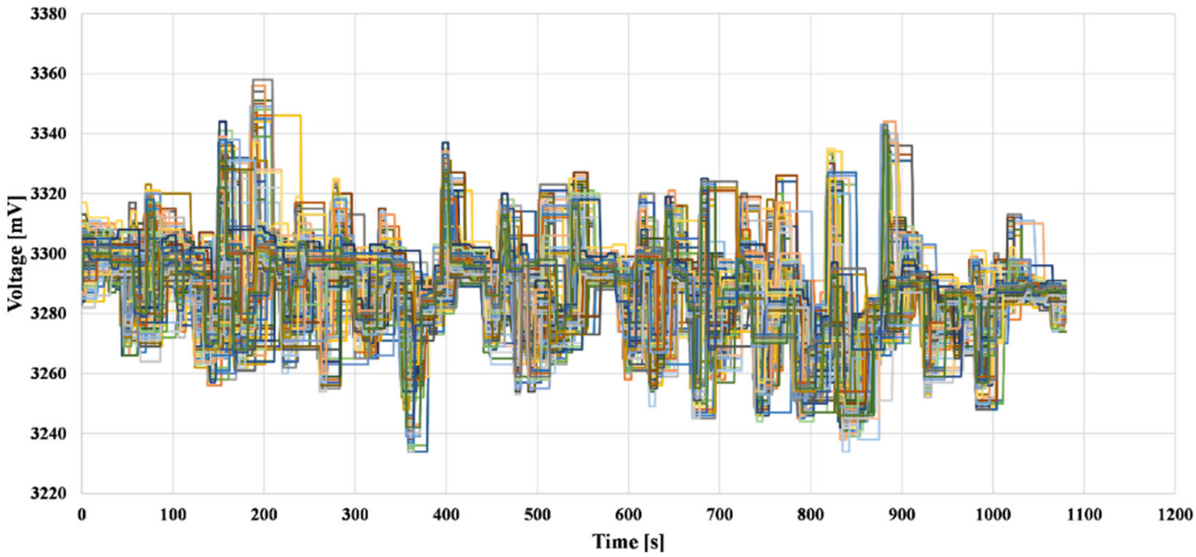

Figure 11. The voltage of all cells in the system during the first test.

It can be observed (Figure 11) that the voltage values of all the cells in the system have been superimposed. This shows that the voltage variation between 3360 mV and 3240 mV is relatively stable. Also, the variations are of the order of 10 mV. A cell-by-cell analysis of each measurement followed these. For this type of test, the cells are compared to the average voltage one by one over the entire measurement range (according to Equation (3)). In the analysis of the deviations (according to Equation (4)), it was also observed how many times each cell deviated from the average voltage (according to Equation (5)).

Figure 12 shows the 0 mV deviations (mean voltage) of all three systems. The horizontal axis of the figure shows the cell ID, and the vertical axis indicates the number of deviations. For easy comparison, the deviations in terms of number of samples by percent have been plotted in Figure 13.

The deviations are variable, with a lower % followed by a higher %. It can also be observed that for packs one and two, the deviation was smaller between cells with 40 and 80 ID, which reached the other cells in a larger range. However, a consistent divergence was observed for pack three. Further measurements yielded similar results; therefore, the first sections (those containing less information relevant to critical cell assignment) are not presented. Thus, the 20 mV level is analyzed from the measurements, as there are still some discrepancies, and they carry relatively more information compared to the results. The 50 mV deviations are presented in a separate summary for comparability.

The same bus was used for measurement two, and the differences were compared to a level of 20 mV (Figure 14). In this case, the average deviation was around 20%, but it is important to note that this value also represents 2% of the total measurement range. No outliers were at this deviation level, and all battery systems showed similar values.

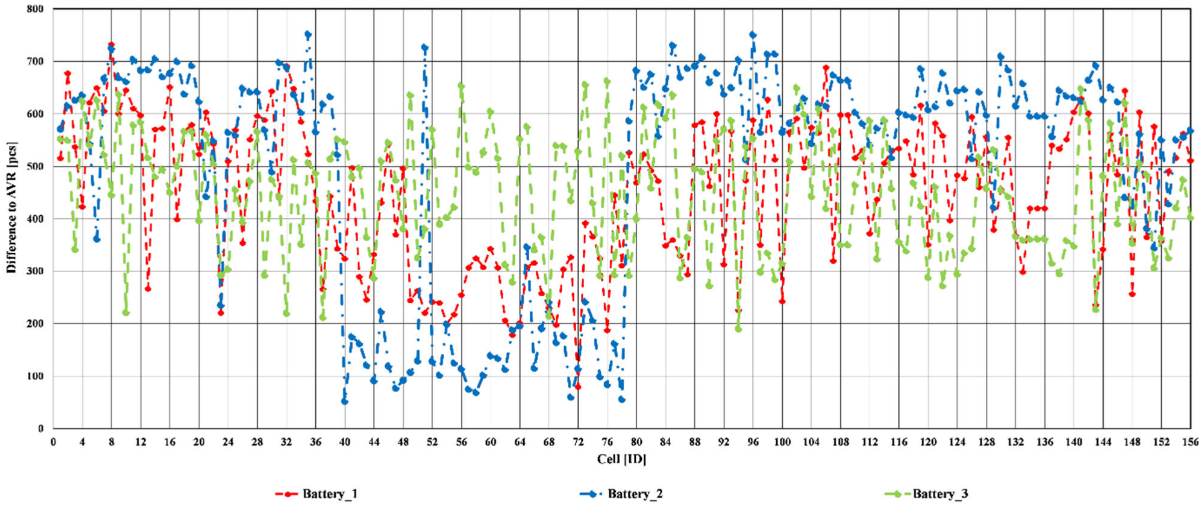

Figure 12. First measurement cell voltage deviations for 0 mV.

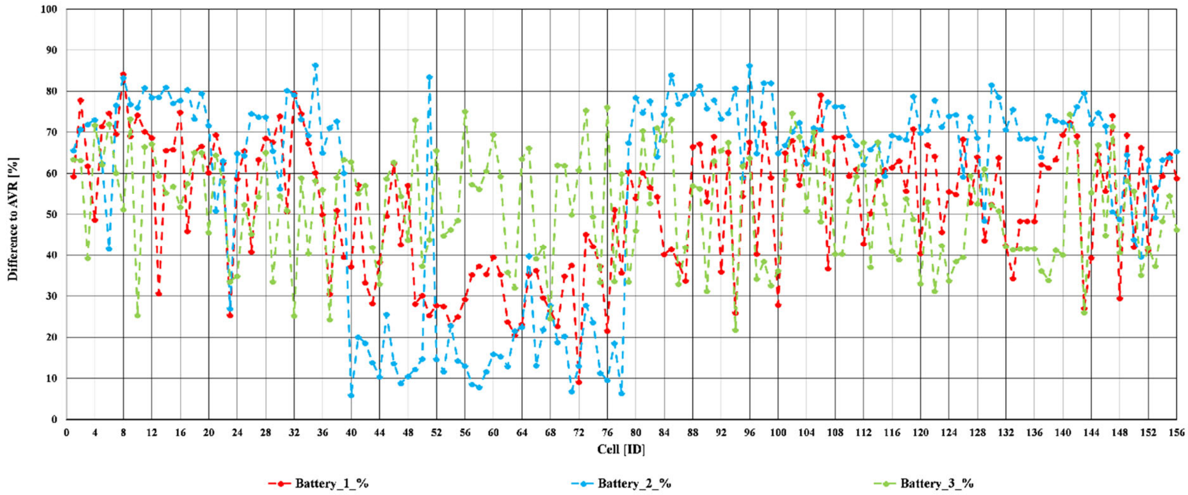

Figure 13. First measurement of cell voltage deviations in % at 0 mV.

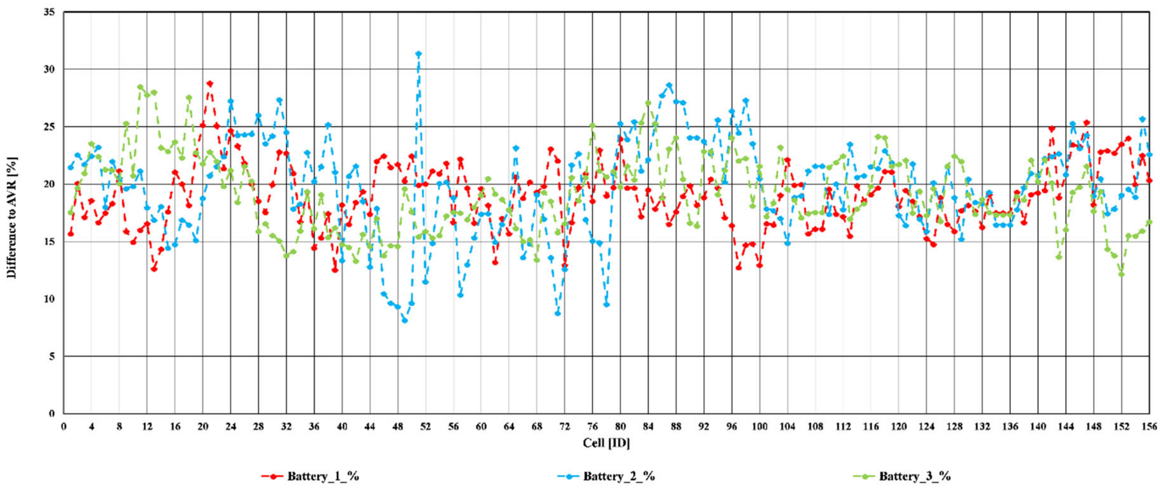

Figure 14. Cell voltage deviations of the second measurement in % at 20 mV.

Figure 15 shows the results of three measurements of the ID-168 bus at 50 mV. It can be observed in the figure that no cell deviated by 5% (critical level) of the total measurement time. The maximum deviation was also below 3%.

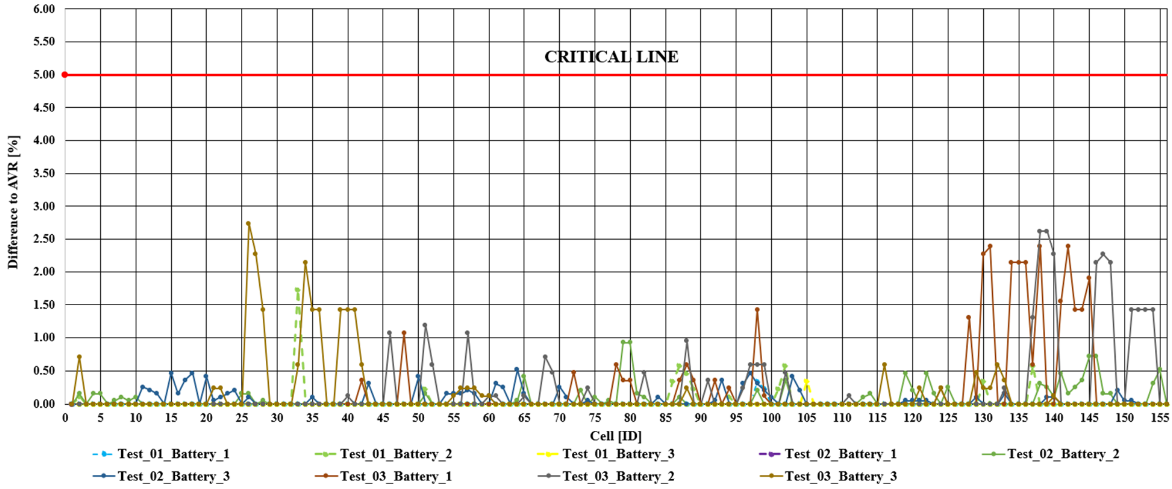

Figure 15. ID-168 electrical bus voltage deviations in % for 50 mV case.

In Figure 16, the values of the ID-174 bus are shown, and in this case, the deviations remained below 3% during the two measurements and for all three battery systems. Overall, the cell voltages in the tested buses showed small deviations. Of course, this could be due to the fact that a new bus battery system was analyzed in both cases. To monitor the changes, it will be worthwhile to repeat this study in a later stage, when the buses have driven more kilometers in 1 or 2 years.

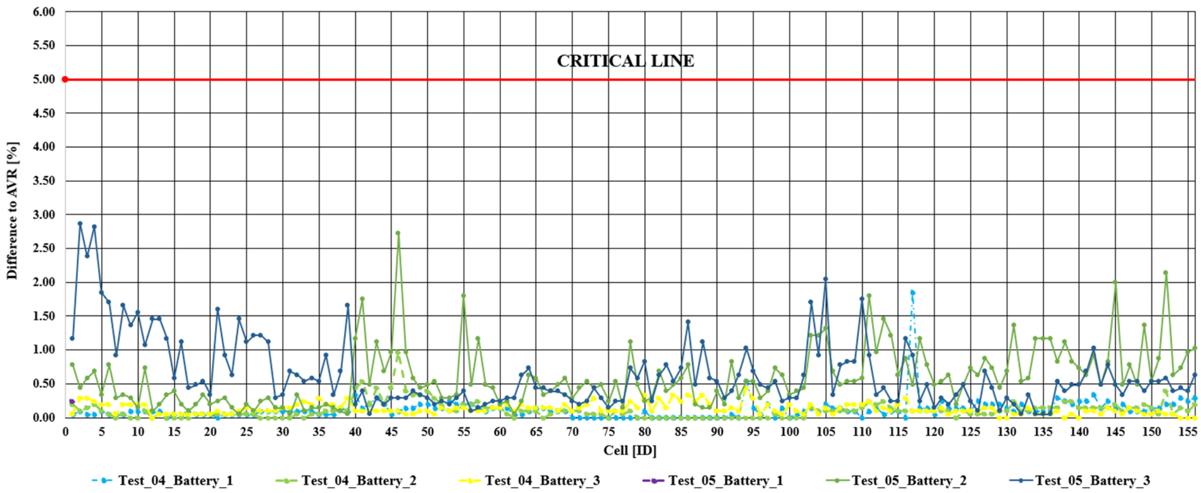

Figure 16. ID-174 electrical bus voltage deviations in % for 50 mV case.

4. Conclusions

The study established that temperature significantly impacts energy consumption. The highest consumption, 116.73 kWh/100 km, was recorded between −5 °C and 0 °C, followed by 106.17 kWh/100 km between 0 °C and 5 °C. A marked decrease in consumption was observed as temperatures rose, with a reduction of 25 kWh between 5 °C and 10 °C, and an additional 10 kWh reduction between 10 °C and 15 °C. Beyond 20 °C, the variations in consumption are more likely due to route differences and driving styles rather than temperature.

Air conditioning use was another significant factor. Turning off the air conditioning during daily stops saved 9.11 kWh (9.34%). However, continuous use was justified for passenger comfort, as extended stops required longer warm-up periods when the air conditioning was turned off. However, it is important to note that this is based on comparing a single measurement, and further measurements are needed to ensure accuracy.

Route and driver variability were also influential. Energy consumption differed by up to three times across routes due to factors like road type, condition, and traffic volume. The analysis found no clear correlation between route length and energy demand. Additionally, there was a 31.85% difference between the most and least efficient drivers, underscoring the importance of driving style over the bus.

The bus battery systems remained in good condition, with a maximum cell deviation of 3%, likely due to the vehicles' newness. However, the continued monitoring of these systems will be essential, especially as the buses age and accumulate more kilometers, to ensure sustained energy efficiency.

This study did not account for the warmest temperature ranges, which could impact energy consumption differently. The influence of passenger load on energy demand was also not included, representing another area for future research. Additionally, all buses in the study were of the same type, limiting the generalizability of the results to other bus models. Future studies should incorporate a broader range of temperatures, bus models, and passenger loads to comprehensively understand energy consumption patterns.

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Nomenclature

EV	Electric Vehicles
BEB	Battery Electric Buses
NMC	lithium-Nickel-Manganese-Cobalt
LTO	Lithium Titanium Oxide
LFP	Lithium Iron Phosphates
SoH	State of Health
SoC	State of Charges
BMS	Battery Management System
CAN	Controller Area Network
Q_{sum}	Total energy consumed
$\overline{V}'_t$	Average pack voltage
AVR_ FLEET	Average consumption for the whole fleet
AVR_BUS	Average value based on all available data for the bus
AVR_DIFF_DRV	Average consumption based on substitute drivers
AVR_BUS_DRV	Average of the two drivers who drive the bus the most
ID	Coded numbers of the drivers
Consumption [kWh/100 km]	Average consumption of the driver
FLEET [kWh/100 km]	Deviation from fleet consumption
cell ID	Number (location) of cells in the battery system

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