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Development of a central fleet monitoring system

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Abstract. Electric buses represent an evolution in the public transportation sector because they provide an innovative and sustainable solution to the pollution and congestion problems that major cities face. However, the bus fleet management system is a complex process that requires monitoring and planning to provide an efficient and reliable public transportation service. In this work, we designed an application that allows us to monitor and evaluate fleet performance data to make informed decisions. Therefore, we have linked the application to a Simulink modelwith the same drive cycle specified for the ring road in Cairo, Egypt and tested it. Early results show a significant potential of the developed system to give useful insights into the influence of monitoring on the electric bus fleet and help to improve decisions-making and the efficiency of the fleet, and extending battery life.

1. Introduction

The transition from conventional transportation systems to electric buses presents a range of significant challenges that necessitate careful consideration and strategic management. It is imperative to identify these challenges systematically and develop targeted approaches to mitigate and address them in a methodical and informed manner. Among the most critical challenges associated with electric vehicles, including electric buses, is the effective maintenance of battery systems and the optimization of battery longevity to ensure sustained operational performance over extended periods.

Although simulation is important and provides valuable predictions, the accuracy of simulation is related to the accuracy of the data entered. Therefore, research in this field uses realistic data taken from real-world scenarios to apply bus traffic on roads, as is the case in this paper. The main focusof simulation is driving cycles, speed profiles, and vehicle mass to estimate the demand for propulsion power.

Wu et al. delved into identifying and measuring various parameters on energy consumption [1]. They also analyzed the factors affecting the all-electric range of electric city buses using real-world operational data. But their vehicle model had a constant speed while varying the vehicle mass and average power of the electric auxiliary. Abdelaty et al. developed a simulation energy model to estimate energy consumption rates and used real Altoona test data [2]. They showed the effects of road conditions, passenger load, driver behavior, speed, and temperature on the energy consumption ofthe electric bus. However, they used fixed values for the auxiliary power demand, which was a large part of the overall demand. Lajunen et al. ran simulations based on typical driving cycles and different climate conditions [3]. Their focus was on reducing energy consumption through predictive driving and improving it. Phyo et al. conducted several scenarios to study the effect of driving behavior on the energy consumption of electric buses [5].

Budiono et al. focused on meeting the needs of the city, which led them to work on the idea of a fleet system [4]. They used simulation with GPS data, but the method was theoretical. Würtz et al. focused on a comprehensive understanding of the factors that affect energy consumption to forecast demand for 16 electric buses [6]. However, the ability to implement control decisions relevant to each case to tackle unscheduled increases in energy demand was not considered. Davydenko et al. has implemented a planning for monitoring EV charging with a situational algorithm and optimizing the electrical load [7]. It is also very detailed in terms of monitoring the power demand of EV-Bus fleet. However, the load (freight) and trip conditions in the case study are deterministic without multiple sources of uncertainty. Astrain et al. provides a well-defined approach for optimal fleet management and control of electric buses in smart cities within the framework of Stardust-Project [8]. The applicability of the proposed solution is significantly subject to the availability of advanced V2V and V2G communication technologies, which adds further requirements to realize this methodology in other urban environments.

In light of the challenges and factors affecting electric buses mentioned, it is important to monitor their impact on E-Buses. So that we can make E-Buses adapt to the changes of these factors. Therefore, this paper presents an application that analyzes the change in these factors and the unexpected conditions that E-Buses may face, monitors their impact on each of state of charge (SoC), capacity loss (C-loss), and energy cooling (E-cooling), then illustrates this in graphs to show the final result. So that we can control and make appropriate decisions based on each situation to maintain the efficiency of the bus and the battery.

The paper is organized as follows: First, a description of the electric bus simulation model and the route it takes in section 2. Second, a clarification of bus fleet management and the need of monitoring, followed by explanation of the application user interface, including a discussion of the factors, and various scenarios that could occur in section 3. Third, analysis of the results of the applied cases in section 4.

2. Vehicle and route modeling

2.1. EV Model

The simulation model used is an E-Bus powered by a couple of hub-permanent magnet synchronous motors (PMSM) [10]. The characteristics of the vehicle are shown in the table 1. The vehicle is modeled with the backward/forward approach as shown in figure 1. Notably, the dataset used for ridership to update the Gross Vehicle Weight (GVW), is based on government reports on ridership along this route [11].

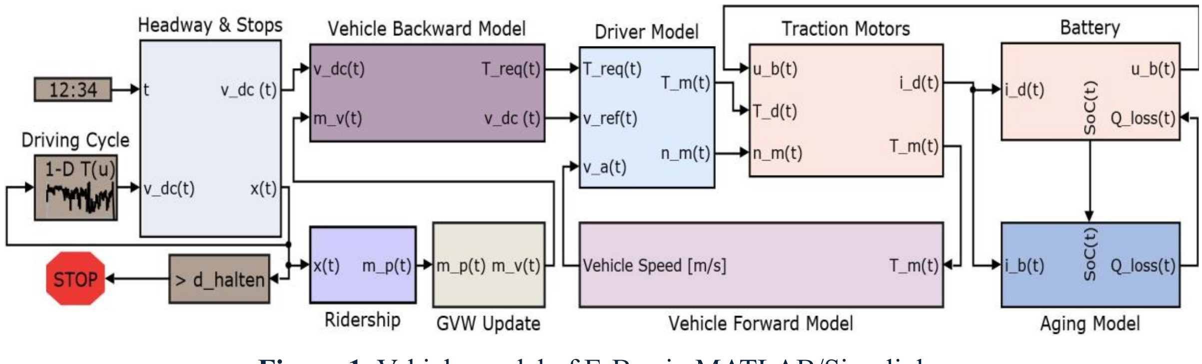

Figure 1. Vehicle model of E-Bus in MATLAB/Simulink

Where the time is t, x distance, and v_{dc} driving cycle velocity. T_{req} requirement torque, m_p passenger mass, and m_v vehicle mass. The reference velocity is v_{ref}, v_a actual vehicle speed, and n_m motor rpm. T_d demand torque, T_m motor torque, i_d demand current, and i_b battery current.

Newton's second law describes dynamic motion. Therefore, the equation of motion of the E-Bus can be represented by summing the forces acting on it, as shown in figure 2 [9].

$$F_{inertia} = F_{trac} - F_{roll} - F_{aero} - F_{grade}, \tag{1}$$

Table 1. Summarized driveline characteristics

Sub-component	Specification		Value	Unit
	Gross vehicle weight	GVW	18,5	[Tonnes]
	Frontal area	A	8.6	[m^2]
Vehicle	Rolling res. coeff.	μroll	0.009	[–]
	Air density	ρair	1.27	[kg/m^3]
	Air drag coeff.	C_d	0.3	[–]
	Tire radius		0.477	[m]
	Seats #		46	[–]
	Pass. capacity		92	[–]
	Battery type		Li-Ion	–
E-driveline	Battery capacity	Q	315	[kWh]
	Battery voltage	u_b	600–650	V
	Motor R. Power		2x150	[kW]
	Motor R. Torque	T_m	2x550	[N.m.]

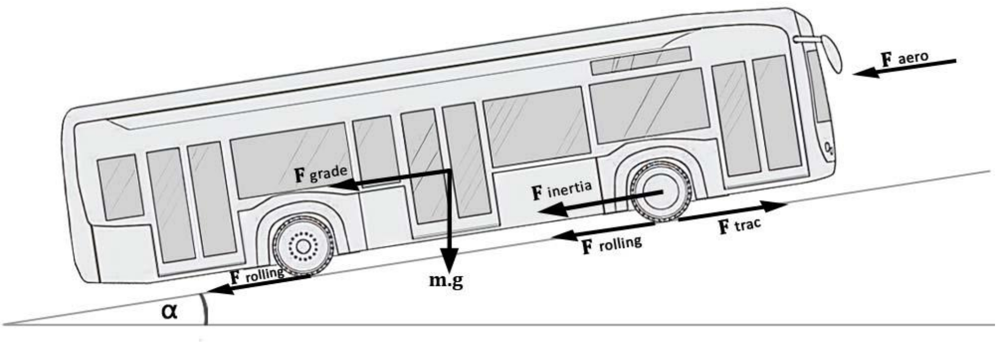

Figure 2. Forces acting on an E-Bus

Then, the tractive effort F_{trac} is calculated based on the speed input from the route driving cycle v as

$$F_{trac} = \underbrace{m\frac{dv}{dt}}_{Inertia} - \underbrace{\frac{A\rho_{air}C_d\bar{v}^2}{2}}_{Air\ drag} - \underbrace{mgsin\alpha}_{Grade\ res.} - \underbrace{\mu_{roll}mgcos\alpha,}_{Rolling\ res} \tag{2}$$

where vehicle mass m is updated regularly according to the ridership information. The frontal area of the vehicle is A, ρ_{air} air density, C_d drag coefficient, and $\bar{v}$ relative wind speed. Gravitational acceleration g and α road grade. Rolling resistance coefficient μ_{roll}.

The PI controller was used in the model to ensure that the load requirements are met [12]. The single-input/multiple-output ($SIMO$) state space model of $PMSM$ was considered as [13]

$$\dot{x} = Ax + Bu, \tag{3}$$

$$y = Cx + Du, \tag{4}$$

for

$$x = \begin{bmatrix} \dot{\theta} \\ i_{mot} \end{bmatrix}, \; u = u_{mot}(t), \tag{5}$$

$$A = \begin{bmatrix} -\frac{d}{\tau} & \frac{T_{eq}}{\tau} \\ -\frac{T_{eq}}{L_{eq}} & -\frac{R_{eq}}{L_{eq}} \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ \frac{1}{L_{eq}} \end{bmatrix}, \tag{6}$$

$$C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad D = [0], \tag{7}$$

where the electromotive torque constant is T_{eq}, τ the rotational moment of inertia, d the viscous friction constant, R_{eq} the equivalent circuit resistance, u_{mot} applied motor voltage, and L_{eq} the equivalent inductance.

Actual vehicle speed is calculated using forward vehicle module based on delivered motor power and hence is considered into closed-loop control of the driver model [14]. Modeling of the Li-Ion battery is conducted based on a second-order Thevenin as shown in the equivalent circuit in figure 3, whereby the battery voltage u_{bat} is formulated as

$$u_{bat} = E_o - i_{bat}\, R_{bat} - u_{t1} - u_{t2} - \frac{1}{C_{bat}} \int_{t_i}^{t_o} i_{bat}\, dt\,, \tag{8}$$

where battery terminal voltage is denoted $u_{bat}(t)$, the fictive capacitance C_{bat} representing the changes in electromotive force, the internal resistance of the battery is R_{bat}, and the open-circuit voltage $u^{o}_{bat} = E_0$ at no load conditions. The voltage drop across the RC-networks 1 and 2 are represented by u_{t1} and u_{t2} as shown in figure 3. Also, t_i and t_f represent the initial and final simulation times, respectively. The polarization dynamics during charging and discharging is represented through in-line RC-networks as [14]

$$\begin{bmatrix} \dot{u}_{t1} \\ \dot{u}_{t2} \end{bmatrix} = \begin{bmatrix} -\frac{1}{R_{t1}\, C_{t1}} & 0 \\ 0 & -\frac{1}{R_{t2}\, C_{t2}} \end{bmatrix} \begin{bmatrix} u_{t1} \\ u_{t2} \end{bmatrix} + \begin{bmatrix} \frac{1}{C_{t1}} \\ \frac{1}{C_{t2}} \end{bmatrix} i^{*}_{bat}\,, \tag{9}$$

where the equivalent resistance and capacitance of each RC-network are denoted $R_{t1,\,t2}$ and $C_{t1,\,t2}$, respectively.

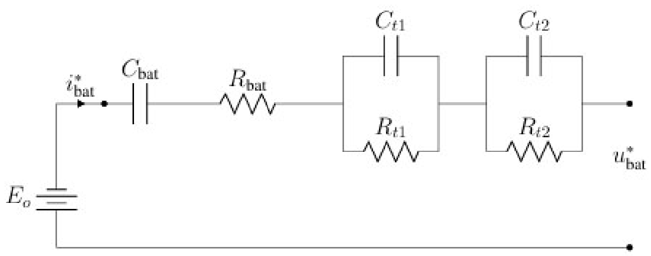

Figure 3. Equivalent circuit model of the battery based on second-order Thevenin model [14]

Degradation of the battery C-loss is modeled based on the validated model in [15] as

$$C_{loss}\,[\%] = (a_1\,.\,SoC_{bat} + a_2)\,.\exp\left(\frac{-E_a + \eta\,.\,I_c}{R_u\,.\,(273.15 + \theta)}\right).\,AH^{a_3} \tag{10}$$

where the activation energy is E_a, R_u universal gas constant, AH the battery throughput, and a_1, a_2, a_3 are arbitrary constants.

2.2. Route Model

The specified route for these E-Buses will be the Ring Road in Cairo, Egypt. So, its driving cycle has been used in the Simulink model to simulate the real. The route is about 80 km long, with specific stop stations to stop on the highway, especially at the exits of the cities. Figure 4 depicts a visual representation of the bus route as well as the zone boundaries [9].

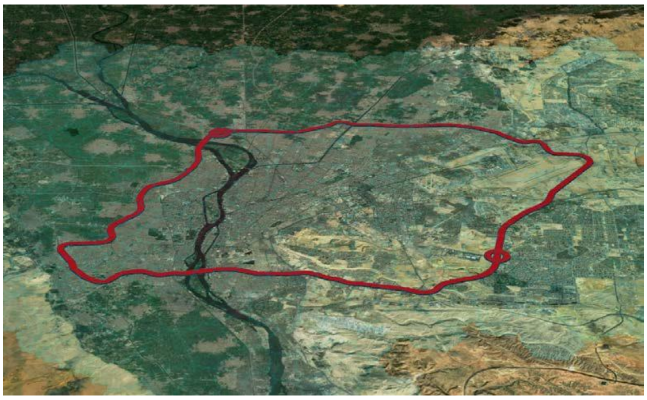

Figure 4. Ring road, Cairo, Egypt

3. Fleet Management System of EVs

3.1. Description of the system

Electric Bus Fleet Management is a comprehensive process that involves monitoring and optimizing the performance of a fleet of electric buses. Integrating it with V2X technology significantly enhances the capabilities of managing EV fleets. To ensure that the buses operate efficiently and sustainably while meeting passenger and operational demands. The main goal of the fleet management system is to maintain the battery life for as long as possible, as it provides detailed information about the status of each battery in the fleet such as charge level, voltage, and temperature [17] [6].

Each E-Bus is equipped with a Battery Management System (BMS) that communicates real-time SoC data to the FMS. It is helpful for optimizing charging schedules to ensure minimal downtime and to receive alerts for low SoC to prevent service interruptions. Also, it leads to reduce the battery capacity loss, which is the gradual reduction in the amount of charge a battery can hold over time due to aging [16].

3.2. User interface of the system

In the SimuLink model, we connect three models of electric buses together. They use the same drive cycle and start from the same point with the consideration of the delays. The second E-Bus starts moving 10 minutes after the first E-Bus, then the third E-Bus starts moving 20 minutes after the first one starts moving. The energy consumption of electric buses varies depending on route attributes, passenger load, and environmental conditions. In the application, we have put the maximum amount of each parameter that the bus can handle with them without harmful effect on the battery. We can also make them deal with unexpected scenarios to avoid any losses and preserve the battery. Figure 5 shows the user interface of the application and illustrates the case 1 of the E-Buses, that will be discussed later.

To illustrate how the application works, on the left there are 3 tuning panels containing the parameters affecting the electric buses. Each E-Bus has a separate panel containing the 3 main parameters: temperature (ΔT), passenger load ($RiGn$) and traffic congestion ($Traffic\ Cond.$). The graphs panel, located on the right, monitors and shows the results of the specified variables. There are five graphs: the first shows the state of charge for each bus; the second shows capacity loss; the third shows electric cooling; the fourth shows vehicle speed and whether the driver is driving on the same specified driving cycle and what his maximum speed is; and the fifth shows the distance traveled by the electric buses. There is also a run button, which launches both the application and the simulation model simultaneously, and the monitoring results are presented on the graphs after specifying the parameters in the tuning panel and sending them to the simulation model.

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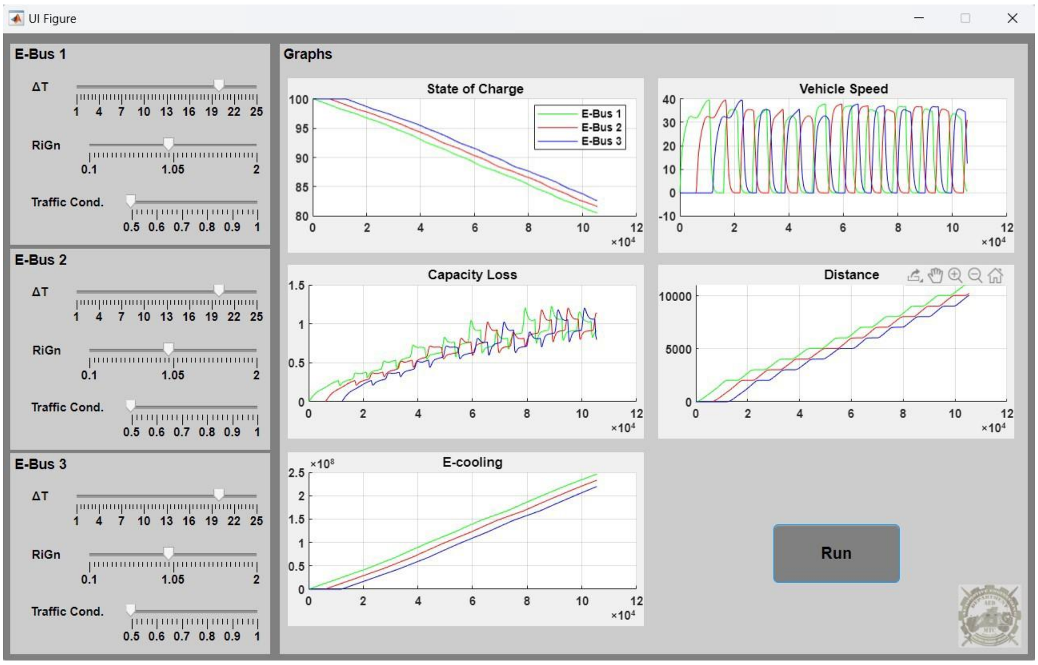

Figure 5. The user interface of the application, the results of case, the results of case 1

Temperature has a significant impact on the battery, as the key to energy consumption is the HVAC system (Heating, Ventilation, and Air Conditioning) [6]. The thermal loads are also varied and include the metabolic energy of the passengers, the ventilation and filtration load, the heat of the engine and the accessories, and the diffuse and radiant heat [9]. As we can see in the app ΔT represents the ambient temperature and ranges from 1⟶25.

$$\Delta T = Exterior\ temperature\ (t_o) - Interior\ temperature\ (t_i) \tag{11}$$

When t_o is 40^o and t_i is 22^o, the ΔT becomes 18.

The passenger load is significantly considered, mostly affecting traction, and also has an impact on the HVAC system [6]. The maximum load that the bus can carry is twice the number of passengers. Therefore, the app shows the load of each one and varies between 0.1 ⟶ 2.

Traffic congestion is one of the factors that is expected, which can linger for up to an hour. It diminishes battery charge and increases capacity loss, even if only marginally. As a result, we replace traffic congestion with a decrease in average route speed. We reduce the average speed by a factor depending on traffic conditions, as shown in the application. Wherefore, we have included it to determine the amount of its impact on the battery and the procedures that should be followed. We can also adjust the charging schedule at that time to reflect the current scenario.

3.3. Description of operating scenarios

Suppose that the temperature on one day is 45^o. E-Buses operate on schedule with fully charged batteries along a single headway. In this paper, the route considered will be only 10 kilometers with ten stop stations. Although the temperature inside each bus is set to 25^o, meaning that ΔT will be 20^0. There is a normal number of passengers on each bus and no traffic congestion. This is **case 1**. To further illustrate the scenarios, we have tuned the three parameters separately to show the impact of each parameter on the C-loss, E-cooling, and SoC. Therefore, table 2 contains the values that were determined for each E-Bus in each case on the application.

Table 2. The values of each parameter for E-Buses in each case on the application

Case	ΔT[^oC]			RiGn[%]			Traffic Cond. [%]		
	E-Bus 1	E-Bus 2	E-Bus 3	E-Bus 1	E-Bus 2	E-Bus 3	E-Bus 1	E-Bus 2	E-Bus 3
Case 1	20	20	20	1	1	1	0.5	0.5	0.5
Case 2	20	20	20	1	2	1	0.5	0.5	0.5
Case 3	20	20	25	1	1	1	0.5	0.5	0.5
Case 4	20	20	20	1	1	1	0.8	0.5	0.5

Another parameter that can be tuned is the delays. We can change the bus departure times according to the imposed circumstances. If this will benefit the public interest, the E-Bus departure time can be brought forward.

4. Exemplified Results and Analysis

The three electric buses in the simulation model operate on the same driving cycle; This driving cycle is real as it is for an actual vehicle to drive on the Cairo Ring Road. Only 10 km of it has been specified, and the maximum speed is 40 [km/h] as shown in figure 6. The graph also illustrates the delays between the E-Buses and their adherence in the Simulink model.

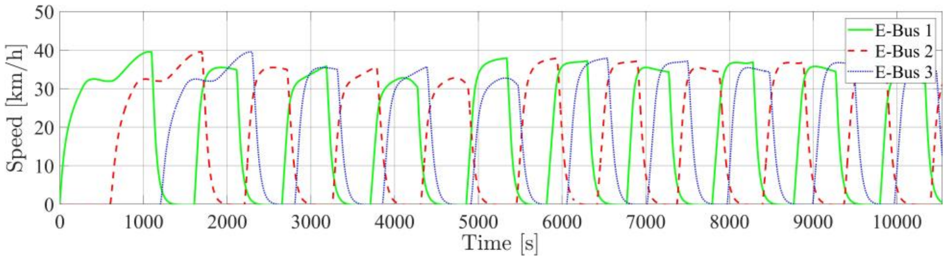

Figure 6. Driving cycle of the E-Buses

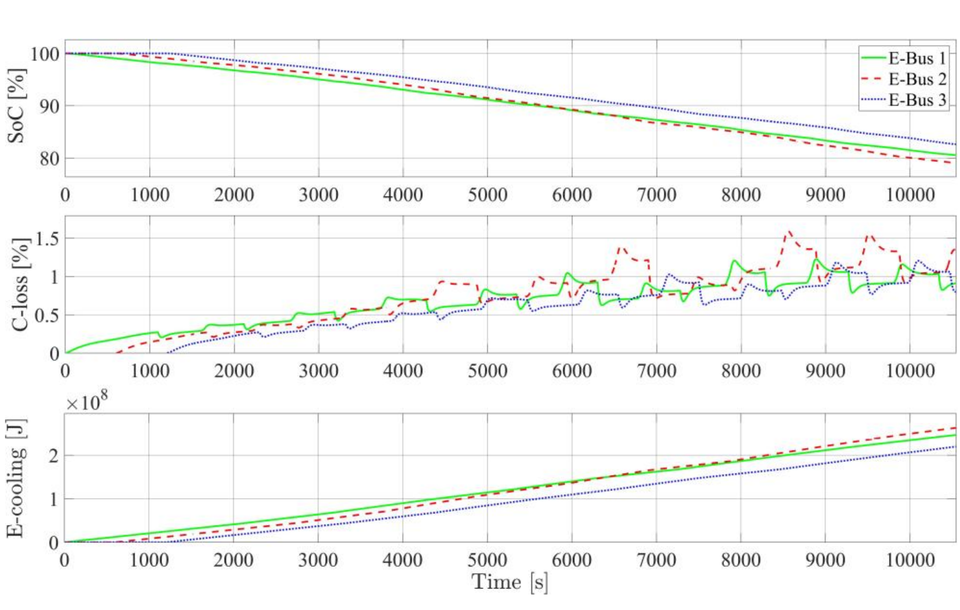

Figure 7. Results of case 2

When case 2 is implemented, We will notice that this affects SoC, C-loss, and E-cooling in figure 7. The ultimate result of SoC will decrease by 2.74 [%] to 77.79 [%], indicating that E-Bus 2 will lose its charge faster than E-Buses 1 and 3. We will also see a slight rise in C-loss (0.0994[%]) and E-cooling ($0.31 \circ 10^8$ [J]). This demonstrates how the passenger load affects the energy consumption of the electric bus. A sudden increase in the number of passengers on the electric bus may result in increased power consumption and brief increases in energy losses. Peaks could appear when the vehicle transitions from braking to accelerating. Energy consumption rises during acceleration, however regenerative braking may temporarily reduce losses before they increase again.

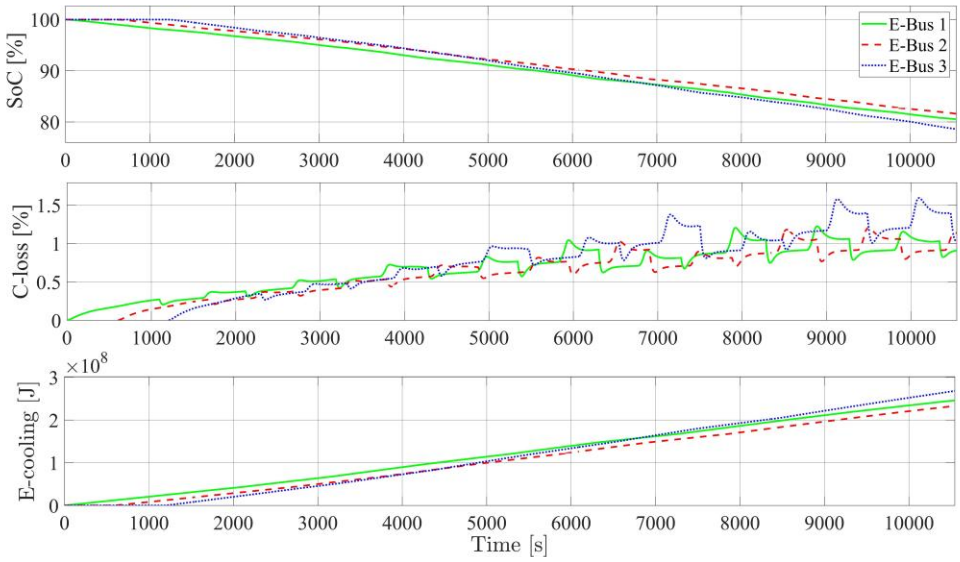

Figure 6. Results of case 3

However, the effect of temperature is more obvious than in the other cases as shown in figure 8. In case 3, C-loss and E-cooling values grow more than in earlier cases. C-loss increases by 0.2594 [%] reaching 1.17 [%], while E-cooling increases by 0.54 to 3 10^8 [J]. In addition, the SoC will decrease faster than in cases 1 and 2, dropping from 80.53 [%] to 76.04 [%]. Similar to case 2, power efficiency may be briefly impacted and losses may increase if the temperature changes. It also causes peaks due to acceleration and braking.

When there is traffic congestion, the battery is not much impacted as shown in figure 9. The SoC will decrease by 1.23 [%], resulting in a final result of 79.3 [%]. Furthermore, its impact on both C- loss and E-cooling is negligible, approaching 0.01. But due to repeated braking and acceleration, traffic congestion raises C-loss peaks. Passive losses are further exacerbated by prolonged idling with power use. In crowded situations, these factors produce abrupt peaks, while smoother operation produces lesser oscillations.

Table 3. The final results of the cases of all E-Buses

Case	SoC_f [%]			C-loss [%]			E-cooling[*10^8] [J]		
	E-Bus 1	E-Bus 2	E-Bus 3	E-Bus 1	E-Bus 2	E-Bus 3	E-Bus 1	E-Bus 2	E-Bus 3
Case 1	80.53	80.53	80.53	0.9106	0.9106	0.9106	2.46	2.46	2.46
Case 2	80.53	77.79	80.53	0.9106	1.01	0.9106	2.46	2.77	2.46
Case 3	80.53	80.53	76.04	0.9106	0.9106	1.17	2.46	2.46	3
Case 4	79.3	80.53	80.53	0.9203	0.9106	0.9106	2.45	2.46	2.46

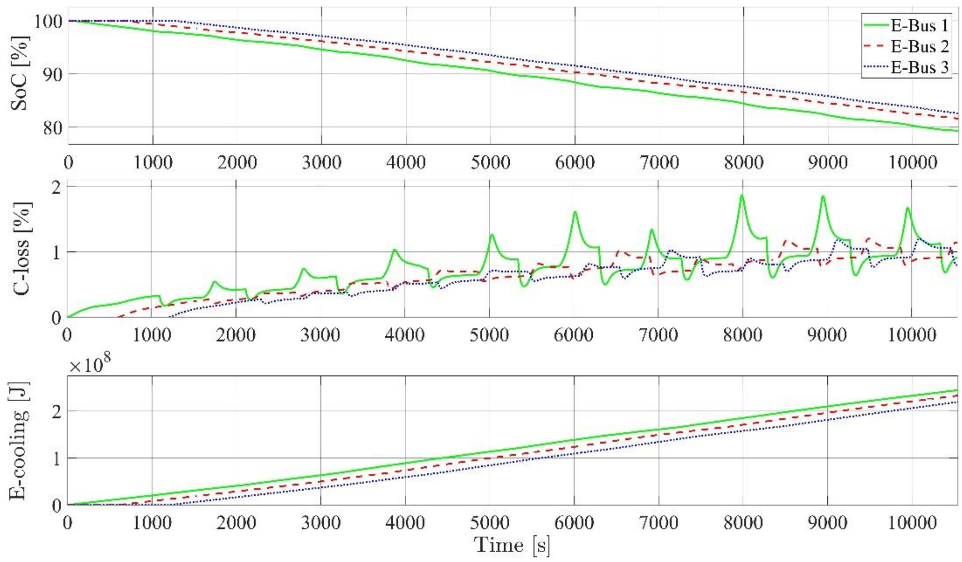

Figure 7. Results of case 4

After investigating the studied cases, we will discover that tuning the parameters has an impact on SoC, capacity loss, and Energy cooling, even if the effect is minimal. As a result, this application monitors these factors and their impact on the E-Buses, and illustrates this in graphs to show the final result. This makes it straightforward to predict effective solutions for these scenarios and make them adapt to the conditions they are exposed to. The ultimate goal is to maintain fleet efficiency.

5. Conclusion

This paper presented an application related to a simulation model for a fleet of electric buses moving on a real drive cycle of the ring road in Cairo. The application showed the final results in graphswhen changing the conditions and factors affecting each electric bus individually, from temperature and passenger load and when traffic congestion occurs. To show the importance of monitoring these influential factors to increase the efficiency of the fleet by knowing and anticipating the conditions and taking effective solutions for that. The importance of monitoring in electric bus fleet management is ensured through the application, as the final results appear according to the scenarios that each bus may be exposed to. It also helps in decisions-making based on these results, such as improving charging schedules, extending battery life, and enhancing efficiency through better energy management. Future improvements of the current work include updating the app user interface control with additional parameters. Also, implementing it to hardware sensors.

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