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Modeling and Comparative Analysis of the Impact of Driving Cycles on Battery State of Charge Performance and Electric Vehicle Driving Range

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The escalating proliferation of electric vehicles (EVs) as a pivotal solution to address energy consumption and air pollution challenges within the transportation sector necessitates a comprehensive understanding of the factors influencing their performance and driving range. Among these factors, driving patterns exert a direct and significant impact on energy consumption and battery state. This study aims to quantify the influence of diverse driving cycles on the performance of an electric vehicle, specifically the Audi e-tron 50. Utilizing Simcenter Amesim software, a longitudinal vehicle dynamics model, coupled with an equivalent circuit model (ECM) for the lithium-ion battery, was developed for simulation purposes. The vehicle's performance was evaluated under five distinct driving cycles, including global standards (WLTC, NEDC, HWFET) and two real-world driving cycles recorded in Tehran (Route1, Route2). Key parameters such as state of charge (SoC), depth of discharge (DoD), battery temperature, and estimated driving range were analyzed. The results revealed a significant impact of driving cycles on all investigated parameters. Driving cycles characterized by higher speeds and accelerations (e.g., WLTC and HWFET) led to increased specific energy consumption, accelerated temperature rise, and a notable reduction in estimated driving range (with the lowest range observed in WLTC). Conversely, milder urban driving cycles (particularly Route1) resulted in improved energy efficiency, minimal thermal stress, and the highest estimated driving range. These findings underscore the critical importance of considering real-world and localized driving patterns for accurate performance evaluation, range estimation, and the development of optimized energy management strategies in electric vehicles.

1. Introduction

Considering the critical value and scarcity of energy resources, optimal consumption management is essential[1]. One of the greatest challenges associated with energy consumption is the increasing emission of greenhouse gases (GHGs), which has intensified with population growth and industrial activities [2,3]. The transportation industry, accounting for approximately 21% of global energy consumption, has a significant share in this challenge [4].

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Therefore, reducing reliance on internal combustion engines (ICEs) due to their low efficiency is considered a key solution for decreasing energy consumption and pollution. Although a major portion of the world's energy is still supplied by non-renewable sources such as oil, coal, and natural gas, strategies such as reducing vehicle weight, increasing energy efficiency, improving fuel quality, developing new technologies, and strengthening sustainable public transportation can contribute to the realization of a clean transportation system [5]. Among these, all-electric transportation systems have garnered special attention at both public and industrial levels. However, challenges such as the limited driving range of electric vehicles (EVs) further emphasize the importance of developing and evaluating optimal control strategies. These strategies are designed with the aim of reducing energy consumption, increasing efficiency, and consequently reducing greenhouse gas emissions. Therefore, continuous review and improvement of these solutions is a fundamental step towards achieving sustainable and environmentally friendly transportation. The global trend in research in recent years has leaned towards the development of vehicles with alternative and renewable fuels instead of internal combustion engines. In this direction, electric vehicles (EVs) are recognized as the flagbearers of clean transportation because, unlike their gasoline and diesel counterparts, they do not emit any direct pollutants (such as sulfur, carbon, or nitrogen compounds) during operation [6,7]. The appeal of electric vehicles is not limited to their cleanliness; high energy efficiency, better controllability, and the ability to provide the required torque without a gearbox are other prominent technical advantages that paint a bright future for them in the transportation industry [8]. Nevertheless, significant challenges also exist in the path to the long-term sustainability and efficiency of electric vehicles, which are mainly attributed to their vital component, the battery pack [9]. Optimal battery design and performance are determining factors not only in the driving range and power of the vehicle but also in its economic aspects and lifespan [10]. Among these, lithium-ion batteries (LIBs), due to their excellent characteristics such as high energy density, lightweight, long cycle life, low self-discharge rate, and suitable charging speed, have become the gold standard for energy storage in modern electric vehicles and play a fundamental role in improving the overall efficiency of these vehicles. Consequently, with the increasing demand for EVs, a large portion of research is focused on optimizing their performance, especially in the field of energy management and increasing battery lifespan [11]. High performance and long lifespan are two key factors for customer satisfaction in all modern vehicles. In the field of electric vehicles (EVs), these two factors are heavily influenced by the battery's condition. For this reason, the accurate estimation of the battery's "State of Charge" (SoC) and "State of Health" (SoH) has garnered widespread attention in scientific and industrial circles worldwide. These two vital parameters play a decisive role in the efficiency, driving range, and overall durability of electric vehicle batteries, highlighting the necessity for their precise evaluation. Accurate monitoring of SoC and SoH not only optimizes the daily performance of the vehicle but also provides essential information for long-term decisions such as battery replacement scheduling and maintenance programs. Ultimately, these metrics are crucial for the optimal use of battery energy, enhancing overall vehicle performance, and ensuring the economic and environmental sustainability of electric transportation [12].

1.2 State of Charge (SoC): The Electric Vehicle's Fuel Gauge

The State of Charge (SoC) is a key indicator that shows electric vehicle (EV) users the amount of energy remaining in the battery, functioning similarly to a fuel gauge in traditional vehicles[13]. Accurate knowledge of the SoC is essential for important decisions such as planning for recharging and estimating the distance that can be traveled with the current charge. Furthermore, correct SoC assessment helps to optimize the utilization of the battery's capacity and contributes to increasing the battery's lifespan by preventing overcharging or deep discharge. Real-time SoC information allows drivers to plan their trips more efficiently, manage their energy consumption patterns, and minimize the risk of sudden charge depletion. Therefore, accurate SoC monitoring is vital for enhancing reliability and improving the user experience in electric vehicles [14,15].

Despite significant advancements in electric vehicle (EV) technology, challenges remain, particularly in the areas of optimizing battery charging and managing energy consumption during driving. Of course, previous studies (such as Hamza et al.) [16] have confirmed that electric vehicles possess inherent advantages over internal combustion engine vehicles regarding energy efficiency and emission reduction. However, developing intelligent energy management strategies is essential to fully realize this potential. Recent research by Du et al. and Rezaei et al. [17,18] has shown that such strategies can significantly reduce energy consumption and extend battery lifespan. The success of these systems hinges on their ability to make optimal and dynamic decisions based on instantaneous driving conditions and accurately predict driver behavior. In this regard, the importance of using real-world driving data is highlighted, as demonstrated by the study of Zhang et al. (2021) [19]; leveraging driving cycles extracted from real data significantly improves the performance of machine learning algorithms in predicting future driving conditions. In addition to energy management, a review of previous studies indicates that the cost of diagnostic systems and the phenomena of wear and tear of components (especially the battery) are also significant challenges for electric vehicles.

Given the increasing global demand for personal vehicles and the environmental consequences of fossil fuel consumption and greenhouse gas emissions, the transition to cleaner transportation systems, including electric vehicles (EVs), is of paramount importance. The transportation sector contributes significantly to greenhouse gas emissions. Although EVs offer a promising solution for reducing emissions and possess technical advantages like high energy efficiency, their performance is heavily influenced by crucial factors such as battery health and driving patterns.

Previous studies have highlighted the importance of using real-world driving data to assess EV performance and develop energy management strategies. However, limited research has specifically investigated the simultaneous impact of these factors under the distinct traffic patterns of megacities like Tehran. Therefore, this research aims to comprehensively examine the effect of different driving patterns (including global standard cycles and real-world Tehran cycles) on the propulsive

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performance, energy consumption, battery State of Charge (SoC), battery temperature, and Depth of Discharge (DoD) of EVs under actual Tehran driving conditions.

This study focuses on the Audi e-tron 50 to provide a deeper understanding of the key factors affecting the efficiency and sustainability of electric vehicles. It utilizes longitudinal dynamic simulation in Simcenter Amesim software and an equivalent circuit model for the lithium-ion battery. The results of this research are expected to contribute to the development of energy consumption optimization and battery management strategies tailored to real-world driving conditions.

2. Modeling

This study focuses on the simulation and analysis of the dynamic performance of an electric vehicle (EV) utilizing Amesim software.

The vehicle's performance was initially assessed based on the Worldwide Harmonized Light Vehicles Test Cycle (WLTC). Subsequently, these results were compared with those obtained from the New European Driving Cycle (NEDC) to achieve a better understanding of the vehicle's behavior under various urban conditions. These standard driving cycles were selected due to their more accurate reflection of real-world traffic and road conditions. The technical specifications and key parameters of the reference EV are presented in Table 1.

Table 1: Specifications of the Audi e-tron 50 Vehicle

Parameter	Value	Unit
Vehicle dimensions (L/W/H)	4901/1935/1616	Mm
Mass	2445	Kg
Maximum Motor Torque	540	N.m
Maximum motor Power	230	kW
Vehicle aero drag	0.28	
Vehicle front area	2.65	m^2

3. Longitudinal Dynamics

This section is dedicated to evaluating the power and energy requirements of the vehicle's powertrain based on the physical principles governing motion. Accordingly, the analysis focuses on the dominant resistive forces, namely aerodynamic drag, rolling resistance, and grade resistance.

It should be noted that within this study, consideration is limited to longitudinal forces acting on the vehicle, although numerous forces are present under real-world conditions. Among these, F_R represents the rolling resistance force, while F_J, F_D, and F_s denote the resistive forces due to acceleration (inertia), aerodynamic drag, and road slope, respectively. These forces play a fundamental role in calculations related to the vehicle's energy and power requirements and are, therefore, of great importance in the optimal design of the powertrain system for electric vehicles [20,21].

$$F_T = F_R + F_J + F_D + F_s \tag{1}$$

$$F_R = C_R \times Mg\ \mathrm{Cos}(\alpha) \tag{2}$$

$$F_J = M\ \frac{dv}{dt} \tag{3}$$

$$F_D = \frac{1}{2} C_D \rho A (V_{rel} + V_{air})^2 \tag{4}$$

$$F_S = Mg\ \sin(\alpha) \tag{5}$$

$$P_R = F_T \times V_{max} \tag{6}$$

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$$E_{Battery} = P_R \times t = C \times V \qquad (7)$$

Several factors influence the amount of resistive force acting on a vehicle while in motion, among the most important of which are the vehicle's mass (M) and the rolling resistance coefficient (C_R). Additionally, the drag coefficient (C_D) and air density (ρ) directly affect the aerodynamic drag force, and the vehicle's frontal area (A) is also a key factor in calculating this force. Furthermore, the vehicle's instantaneous speed (V_{rel}) and its maximum achievable speed (V_{max}) determine the amount of power required to overcome these resistive forces. To supply this power, the energy stored in the battery pack ($E_{Battery}$) must be sufficient to provide the vehicle's required power (P_R) for a specific duration (t). Finally, the battery capacity (C), measured in Ampere-hours (A.h), and the battery pack voltage (V) also influence the total amount of storable energy and, consequently, the vehicle's driving range.

4. Battery

The 2022 Audi e-tron 50 quattro[22], with its 71.2 kWh configuration, offers an engineered and optimized structure for electric performance. Equipped with a lithium-ion battery and a usable capacity of 64.7 kWh, this vehicle can achieve a range of 336 kilometers (according to the WLTP standard). The battery pack consists of 324 cells organized into several modules (108s3p). These modules are designed to enhance safety, thermal management, and repairability, and they help maintain a voltage of 400 volts. This modular structure increases energy density and optimizes battery cooling under various conditions. An equivalent circuit model has been used for battery modeling in this research.

Table 2. Battery Pack Specifications [22]

Parameters	Value	Unit
Pack Capacity	71.2	kWh
Pack power	230	kW
Pack Voltage	400	V
Cell Capacity	60.537	Ah
Total mass of cell	580	kg
Number of cells in Parallel	3	-
Number of Cells in Series	108	-

4.1 Modeling Battery Dynamic Behavior Using an Equivalent Circuit Model (ECM)

Equivalent Circuit Models (ECMs) [23] are employed to describe and predict the dynamic behavior of batteries, particularly at the battery pack level. By combining lumped elements like resistors and capacitors, these models can simulate battery performance under various operating conditions, including different discharge rates, temperatures, and states of charge (SoC). The main advantages of using ECMs lie in their simplicity, ease of implementation, and the relatively small number of adjustable parameters required, making them a common choice in many studies and simulations [24]. Despite their simplicity, these models can represent the dynamic behavior and governing equations of the battery with reasonable accuracy. The ability of ECMs to predict performance makes them highly valuable for the optimal design of battery packs in specific applications, such as electric vehicles (EVs) or power tools. Various types of ECM structures can be utilized. In modeling battery packs, it is often assumed that all the constituent cells of the pack are identical. This assumption allows the combined effects of the cells, along with additional

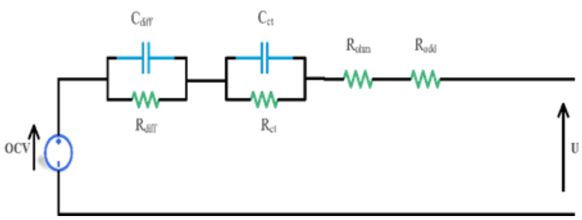

Figure 1: Schematic of the Battery Equivalent Circuit

resistances arising from internal connections and other components, to be represented by a single equivalent circuit (as shown in Figure 1).

In Figure 1, the additional resistance (R_{add}) depends on the number of series and parallel cells and the cell parameters. To calculate the State of Charge (SoC), the following relationship is used [25]:

$$\frac{dSOC}{dt} = 100 \times \frac{I}{Q'} \times \eta_{\text{farad}} \tag{8}$$

where Q' is the available battery capacity in Ampere-hours. Additionally, to calculate the overall voltage drop, the additional resistances are taken into account:

$$\Delta U_{\text{add}} = -I \times R_{\text{add}} \tag{9}$$

Other voltage drops, including hysteresis drop (ΔU_{hyst}), ohmic drop (ΔU_{ohm}), charge transfer drop (ΔU_{ct}), and diffusion drop ΔU_{diff}, are expressed by the following relationships, respectively:

$$\Delta U_{\text{hyst}} = OCV_{\text{eq}} - OCV \tag{10}$$

$$\Delta U_{\text{ohm}} = -I \times R_{\text{ohm}} \tag{11}$$

$$\Delta U_{\text{ct}} = -I \times R_{\text{ct}} \tag{12}$$

$$\Delta U_{\text{diff}}^{\text{total}} = \sum_{i=1}^{N_{\text{RC}}} \Delta\, U_{\text{diff}}[i] \tag{13}$$

Therefore, the total voltage drop is calculated as follows:

$$\Delta U_{\text{total}} = \Delta U_{\text{add}} + \Delta U_{\text{hyst}} + \Delta U_{\text{ohm}} + \Delta U_{\text{ct}} + \Delta U_{\text{diff}}^{\text{total}} \tag{14}$$

This equivalent circuit model contributes to the accurate analysis and prediction of battery pack performance under various operating conditions.

4. Driving Cycle

A driving cycle is defined as a speed-time profile representing a characteristic driving pattern within a specific environment, such as urban or highway conditions. These cycles serve as fundamental tools for analyzing and evaluating vehicle performance, particularly for electric vehicles (EVs), under diverse operational conditions[26]. Driving patterns and their corresponding cycles exhibit significant variability across different regions due to disparities in factors, including road infrastructure, route types, vehicle fleet composition, traffic conditions, driving culture, socio-geographical characteristics, and urban scale. This inherent diversity underscores the importance of selecting or developing appropriate driving cycles that accurately represent real-world conditions for vehicle performance studies, particularly for the design and evaluation of energy management strategies. Consequently, to gain a more precise understanding of electric vehicle performance, simulations are commonly employed to evaluate the vehicle's dynamic behavior under standard or locally developed driving cycles [27]. In the present study, to achieve a comprehensive evaluation, the performance

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of the subject electric vehicle is analyzed and compared using a suite of international standard driving cycles—including the Worldwide Harmonized Light Vehicles Test Cycle (WLTC), the New European Driving Cycle (NEDC), and the Highway Fuel Economy Test cycle (HWFET)—alongside several specific driving cycles derived for the Tehran metropolis. This approach facilitates the examination of the vehicle's behavior across a broader spectrum of driving patterns and conditions.

4. Model Validation

Figure 1 presents four bar charts that offer a comprehensive comparison between the simulated values of the developed model and the declared values for four key performance criteria of an electric vehicle. This comparison aims to validate the accuracy of the simulation model in predicting the dynamic behavior and energy consumption of the vehicle, based on official and standard information. As observed in the charts, for the driving range criterion in the WLTC cycle, the simulated range (340 km) shows a very minor difference of only 4 km compared to the declared range (336 km) under low energy conditions of the WLTC test. This indicates the model's excellent accuracy in predicting the vehicle's real driving range

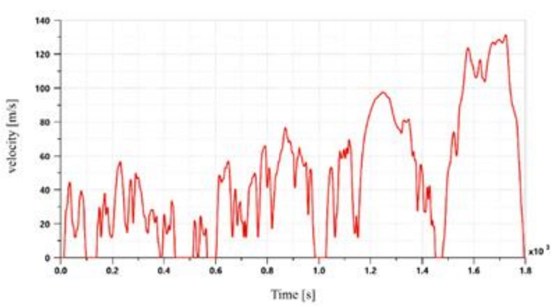

Figure 2: WLTC

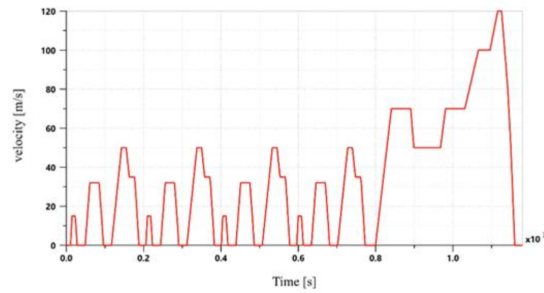

Figure 3: NEDC

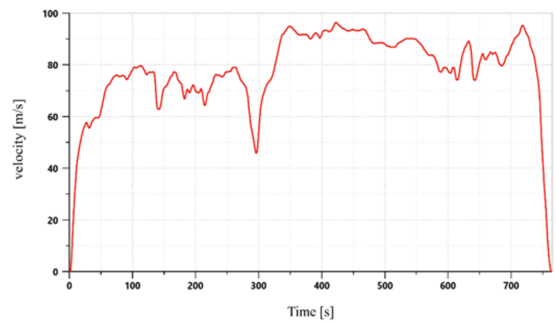

Figure 4: EPA Highway Fuel Economy Cycle HWFET

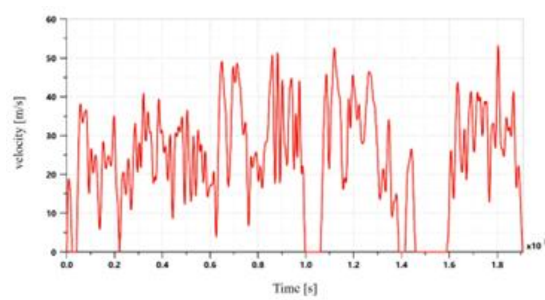

Figure 5: Route 1

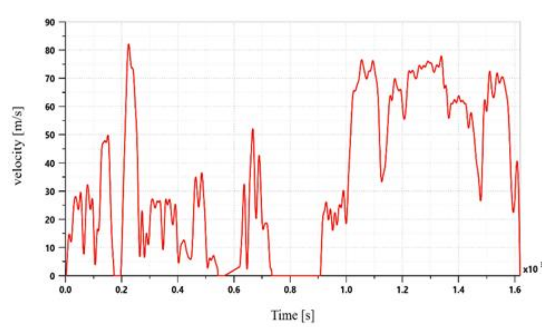

Figure 6: Route 2

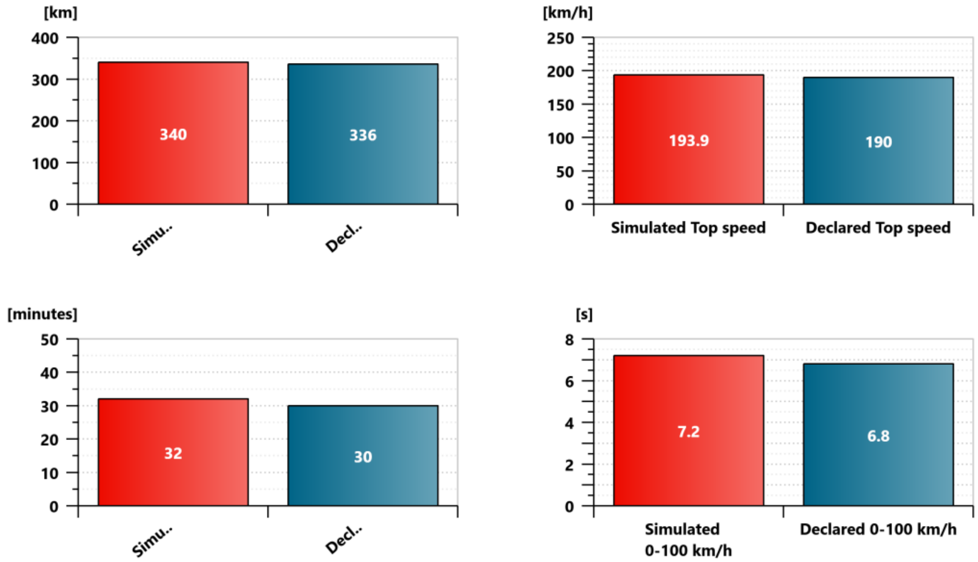

Figure 7: Comparison of four key electric vehicle performance metrics with simulated results versus declared values.

under a standard cycle, significantly enhancing the model's credibility in evaluating energy consumption and driving range. Regarding maximum speed, the simulation model predicted a maximum speed of 193.9 km/h, while the declared value is 190 km/h. This relatively small difference (approximately 3.9 km/h) still demonstrates a strong correlation between the model and reality. Possible reasons for this discrepancy could include minor differences in aerodynamic coefficients or rolling resistance used in the simulation compared to actual measurement conditions. In terms of charging time (0% to 80% with a 120 kW DC charger), the simulated charging time is 32 minutes, and the declared charging time for the same conditions is 30 minutes. This small difference, which is less than 7%, indicates that the model is capable of adequately simulating the battery charging process and its thermal management during fast DC charging. Minor discrepancies may arise from more precise charging curves, initial battery temperature, or the efficiency of the charging system under real conditions.

Finally, for 0-100 km/h acceleration, the simulated time is 7.2 seconds, and the declared time is 6.8 seconds. This difference is also relatively small (0.4 seconds) and demonstrates the model's ability to simulate vehicle dynamics and powertrain performance, where factors such as exact vehicle mass, road friction, or the instantaneous response of the motor and gearbox could play a role in this minor difference. Overall, the comparison between the simulation results and the declared data demonstrates a very good agreement of the developed model. The high accuracy in predicting driving range, along with a strong correlation in predicting maximum speed, charging time, and acceleration, strongly confirms the model's validity for use in future studies, parameter optimization, and evaluating various performance scenarios of electric vehicles. This validation is an important step towards trusting the results obtained from modeling and simulation in the design and analysis process of electric vehicles.

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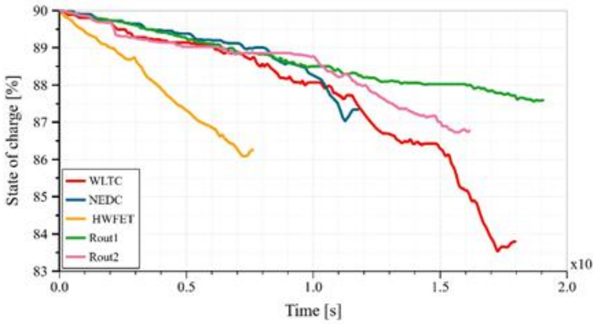

Figure 8: Comparison of battery SoC over time under five different driving cycles.

Given that the simulated electric vehicle is fully electric and the battery pack acts as its sole energy source, the overall performance of this vehicle is directly related to the actual state of the battery. Furthermore, how electric vehicles consume energy in real-world driving conditions is also a determining factor. The simulation results are presented in detail below.

Figure 8 illustrates the evolution of the battery's State of Charge (SoC) over time for the five driving cycles under investigation (WLTC, NEDC, HWFET, Route1, and Route2). The vertical axis represents the SoC percentage, and the horizontal axis represents time in seconds. All cycles start from the same initial charge level, approximately 90%. The general trend of the graph shows a decrease in SoC over time for all profiles, which is due to the energy consumed by the battery to supply the power required by the vehicle's powertrain during the driving cycle. The main difference lies in the decrease in the rate of SoC and the final SoC value at the end of each cycle, which is directly dependent on the power demand of that cycle. Specifically, the HWFET cycle (highway driving simulator), characterized by high speeds and relatively strong accelerations, has the highest average power demand in its short duration; therefore, we observe the fastest rate of SoC decrease in this profile, reaching approximately 86.25% in about 800 seconds. Conversely, the Route1 cycle (one of the Tehran driving cycles), which likely involves lower speeds, gentler accelerations, and more stops, has the lowest average power demand; this results in the slowest rate of SoC decrease and consequently the highest final SoC level (87.6%) among the longer duration cycles. The WLTC cycle consumes the most energy overall, as it covers a wide range of driving conditions, including phases with high speeds and acceleration, particularly towards the end of the cycle, resulting in the lowest final state of charge (SoC) level of 83.8%. The negative slope of the WLTC curve becomes steeper after about 1000 seconds, especially after 1500 seconds, which is due to entering driving phases with higher power demand in the later stages of this standard cycle. The NEDC and Route2 cycles (another Tehran driving cycle), due to having speed and acceleration profiles with moderate power demand, exhibit intermediate rates of SoC decrease and final SoC values (approximately 87.34% and 86.78%, respectively) compared to the other cycles. Therefore, the differences observed in the graph are directly attributable to the differences in the instantaneous and average energy and power required to follow each of these driving patterns.

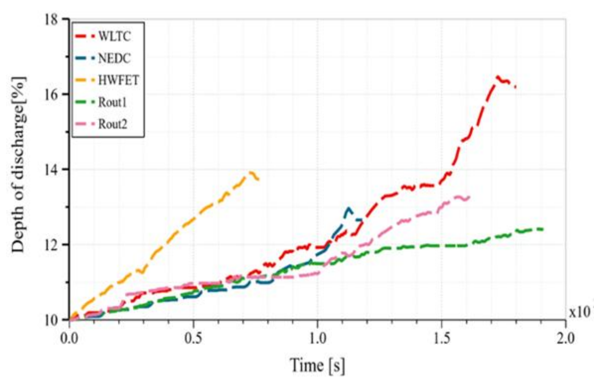

Figure 9: Comparison of battery DoD over time under five different driving cycles

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Figure 9 displays the changes in the battery's Depth of Discharge (DoD) over time for five different driving profiles. These profiles include the standard driving cycles WLTC and NEDC, the highway driving cycle HWFET that simulates driving conditions on highways and open roads, and two defined routes related to driving cycles in the city of Tehran (Route 1 and Route 2). As observed, all tests commence from a similar starting point with a 10% Depth of Discharge. Over time, the DoD increases for all profiles, but the rate of this increase and its final value vary depending on the type of driving profile. The HWFET (highway) profile exhibits the fastest rate of DoD increase in a shorter time frame (up to approximately 765 seconds), reaching about 13.74%, which indicates higher energy consumption per unit of time for this type of driving condition. In contrast, the Route1 profile (one of the Tehran driving cycles) has the lowest slope of DoD increase and reaches the lowest DoD value among the longer duration profiles (12.4%) at the end of the observed time frame (approximately 1910 seconds), suggesting the gentlest energy consumption pattern in that specific traffic condition. The WLTC cycle, which covers the most extended duration, ultimately reaches the highest DoD, over 16.2 %, and the slope of the DoD increase becomes steeper, especially after 1000 seconds. The NEDC and Route 2 profiles (the other Tehran driving cycle) show moderate consumption patterns, ending at approximately 1180 and 1600 seconds, with final DoD values of 12.65% and 13.21%, respectively. These results clearly demonstrate that the driving pattern, whether it is a global standard, real urban traffic conditions like Tehran, or highway driving, has a direct impact on the rate and amount of battery energy discharge, and different cycles can lead to varying levels of stress on the battery.

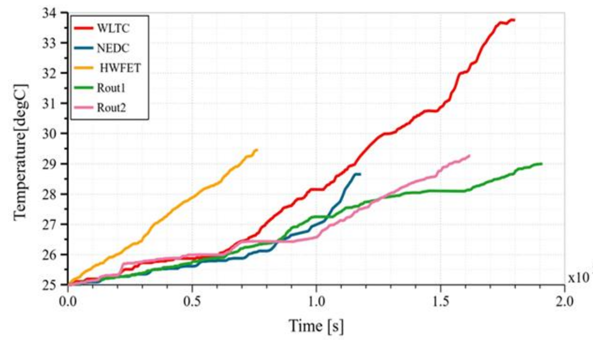

Figure 10: Comparison of battery temperature changes over time under five different driving cycles.

Figure 10 illustrates the battery temperature profile over time for the five different driving cycles (WLTC, NEDC, HWFET, Route1, and Route2) that were previously analyzed in terms of depth of discharge. Observations indicate that the initial battery temperature at the start of all cycles was the same, approximately 25 ℃. However, the rate of temperature increase over time varies for each cycle, indicating the influence of the driving pattern on heat generation within the battery. The HWFET cycle (highway driving simulator), which exhibited a high discharge rate, shows the fastest rate of temperature increase in its short duration (up to about 765 seconds), reaching a temperature of 29.45 ℃. This confirms the correlation between high power demand and greater heat generation. The WLTC cycle, although initially having a gentler temperature increase compared to HWFET, eventually reaches the highest final temperature, close to 34.7 ℃, over the longest duration (1800 seconds). The rate of temperature increase in this cycle notably increases, especially after the 1000-second mark, which aligns with the increased discharge rate observed in the previous chart. Conversely, the Route1 cycle (related to driving in Tehran), which showed the lowest depth of discharge, also has the lowest slope of temperature increase,

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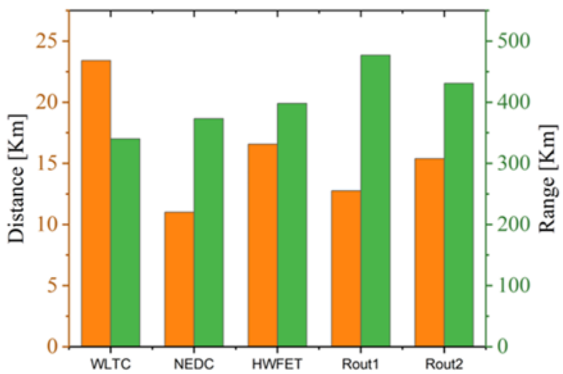

Figure 11: Comparison of Estimated Driving Range of Electric Vehicle Under Five Different Driving Cycles.

reaching a temperature of 29 °C at the end of the time frame, indicating the least thermal stress among the cycles. The NEDC and Route 2 cycles (another Tehran driving cycle) exhibit intermediate thermal behavior, reaching final temperatures of 28.6 and 29.3 °C, respectively. These results emphasize that the characteristics of the driving cycle not only affect the amount of energy consumption but also significantly influence the thermal profile and temperature management of the battery.

The bar chart in Figure 11 compares two key parameters for the five studied driving cycles: WLTC, NEDC, HWFET, Route1, and Route2. The orange bars represent the defined or recorded length of each cycle; for example, the WLTC cycle, at 23.410 kilometers, covers the longest distance among these cycles, while the NEDC, at 11 kilometers, is the shortest. The green bars represent the estimated driving range of the vehicle, typically calculated based on the specific energy consumption (usually in Watt-hour per kilometer - Wh/Km) measured during each test cycle. Analyzing these bars in comparison to the distance bars highlights a crucial point: the energy efficiency and the estimated range are significantly affected by the attributes of the driving cycle. Cycles such as WLTC and HWFET, which have high-speed phases and frequent, strong accelerations, lead to increased specific energy consumption (Wh/Km). This is due to the higher power required to overcome resistive forces (aerodynamic and inertia) at high speeds and accelerations, as well as the lower efficiency of the powertrain system under these conditions. For this reason, despite the longer distance of the WLTC cycle, the resulting estimated range (340 kilometers) is the lowest among the cycles. The HWFET cycle, due to its highway nature and high speeds, also has relatively high energy consumption, resulting in a medium to low estimated range (398 kilometers).

Conversely, cycles like Route1 and, to some extent, NEDC, which represent gentler driving patterns with lower average speeds and smoother accelerations, lead to reduced specific energy consumption and improved energy efficiency. Under these conditions, less energy is consumed per kilometer traveled. The primary reason for the higher estimated range in these cycles, particularly Route 1, which has an estimated range of about 477 kilometers, and NEDC, with an estimated range of approximately 373 kilometers, is improved energy efficiency, even though the NEDC test cycle distance is relatively short. In contrast, Route 2, which features intermediate energy consumption and efficiency characteristics, offers a more moderate estimated range of 431 kilometers. This chart clearly illustrates that driving patterns significantly impact both instantaneous and average energy efficiency, which in turn plays a crucial role in determining the final achievable driving range of an electric vehicle.

4. Conclusion

This research aimed to evaluate the longitudinal dynamic performance and energy consumption of an electric vehicle

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(Audi e-tron 50) under the influence of various driving cycles, using simulation in Simcenter Amesim software and employing an equivalent circuit model for the lithium-ion battery. The analysis of the simulation results on global standard cycles (WLTC, NEDC, HWFET) and real-world driving cycles recorded in the city of Tehran (Route1, Route2) demonstrates the significant impact of the driving pattern on key vehicle performance parameters.

The main findings of this study are as follows:

1. **Energy Consumption and State of Charge (SoC/DoD):** Driving patterns with high speeds and frequent accelerations, such as the HWFET highway cycle and parts of the WLTC cycle, lead to the highest instantaneous energy consumption rates and, consequently, the fastest decrease in SoC and increase in Depth of Discharge (DoD). In contrast, gentler urban driving cycles like Route1, due to lower speeds and smoother accelerations, exhibit the lowest energy consumption and, as a result, the slowest battery discharge rate. These differences emphasize the importance of adapting energy management strategies to real-world driving conditions.

2. **Battery Temperature:** The battery temperature profile is directly related to the energy consumption pattern. Cycles with high power demand (such as HWFET and WLTC) cause a faster increase and reaching higher temperatures in the battery pack, which can affect battery health and lifespan. Milder cycles like Route1 impose the least thermal stress on the battery.

3. **Estimated Range:** The results clearly show that the vehicle's achievable range is highly influenced by the energy efficiency in each driving cycle. More aggressive cycles (WLTC and HWFET), due to higher specific energy consumption (Wh/km), lead to a reduction in the estimated range, with the WLTC cycle yielding the lowest estimated range (340 kilometers) despite its longer distance. Conversely, urban cycles like Route1, by providing the best energy efficiency, enabled the highest estimated range (477 kilometers). This finding highlights the importance of using local and real-world driving cycles for a more accurate assessment of the range of electric vehicles.

Overall, this study demonstrated that the characteristics of the driving cycle, whether standard or real-world, play a decisive role in the energy consumption, state of charge, battery thermal management, and final driving range of an electric vehicle. The results emphasize that considering real driving patterns and local operating conditions is essential for accurately evaluating the performance and optimizing the energy management systems of electric vehicles. Although the initial research objectives included investigating the impact of different battery State of Health (SoH) levels, the analysis of the results presented

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in this section primarily focused on comparing driving cycles. It is recommended that future research comprehensively investigate the combined effect of driving cycles and different SoH levels on performance and energy consumption.

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