

Determination of the Functional End-of-Life Threshold of Electric Vehicle Lithium-ion Battery Under Urban Lagos Driving Conditions

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Abstract

Electric vehicle lithium-ion batteries are typically considered at end-of-life when their State of Health (SoH) falls to 70–80%, a benchmark largely derived from studies in regions with extreme cold climates. This study assesses the relevance of this threshold for electric vehicles operating under consistently warm, urban driving conditions in Lagos, Nigeria. A simulation framework was developed in MATLAB to model energy consumption, power demand, and battery degradation across twelve (12) representative driving scenarios. Results show that, in urban Lagos, battery ageing is driven primarily by depth of discharge, stop-and-go cycling, and daily usage patterns, while the effect of ambient temperature is comparatively minor. Across all scenarios, batteries maintained practical driving capability well below conventional thresholds, remaining functionally viable at 40–60% SoH. These findings indicate that fixed capacity-based criteria underestimate useful battery life in tropical cities. A functional definition incorporating range sufficiency and recharge frequency provides a more appropriate basis for planning, policy design, and EV cost optimisation.

Keywords: Electric Vehicles, End of Life, State of Health, Lithium-Ion Battery, Urban Lagos, Sustainable Mobility.

Introduction

The transport sector accounts for nearly one quarter of global energy-related carbon emissions, making it an essential focus in global decarbonisation efforts (Timilsina *et al.*, 2025). As countries work toward net-zero targets, electric vehicles (EVs) have become a cornerstone of the transition. EV adoption continues to grow at an unprecedented pace, with global sales exceeding 17 million units in 2024 and projected to surpass 20 million in 2025, representing more than 20% of worldwide new car sales ((IEA), 2025). This rapid expansion places increasing importance on the lithium-ion battery (LIB), the component that ultimately determines EV efficiency, usable driving range and long-term performance characteristics (De Cauwer *et al.*, 2015; Ziegler *et al.*, 2020). LIBs remain the dominant choice for EVs because of their high energy density, long cycle life and superior efficiency compared to alternative chemistries (Afia *et al.*, 2024; Alashur, 2024; Asamoah *et al.*,

2024). However, like all electrochemical systems, lithium-ion batteries degrade over time. Their performance declines through interconnected electrochemical, mechanical, and thermal processes that gradually reduce their ability to store and deliver energy. To manage battery life, manufacturers and policymakers commonly classify EV lithium-ion batteries as reaching end-of-life when their State of Health (SoH) declines to 70–80%. This threshold originates largely from laboratory experiments and performance data gathered in cold-climate regions, where low temperatures intensify internal resistance growth and significantly reduce available driving range (Arrinda *et al.*, 2021; Canals Casals *et al.*, 2022; M. Etxandi-Santolaya *et al.*, 2024; Etxandi-Santolaya *et al.*, 2023; Hao *et al.*, 2020; Plotz *et al.*, 2017; Saxena *et al.*, 2015). Yet multiple studies indicate that real-world battery performance does not always align with this convention. Under driving conditions characterised by short trips and frequent stop-and-go motion, batteries may continue to function adequately even below the 70% SoH mark (Arrinda *et al.*, 2021; Canals Casals *et al.*, 2022; De Cauwer *et al.*, 2015; Hao *et al.*, 2020; Plotz *et al.*, 2017; Saxena *et al.*, 2015), emphasizing the need to examine battery behaviour within the specific driving and environmental contexts in which EVs are used.

Such considerations are especially relevant in warm, congested urban environments. Lagos, for example, maintains ambient temperatures between 21 °C and 34 °C throughout the year (Spark, 2025) and exhibits highly dynamic driving patterns shaped by congestion, repeated stopping, short trip lengths and variable road gradients (Nwaigwe *et al.*, 2019; Ojo & Gbadegesin, 2024). These conditions create distinctive cycling behaviours that differ from standard test profiles. Broader factors influencing EV use, such as willingness to participate in smart charging programmes and the role of economic incentives, further shape the operational landscape in such regions. Understanding battery performance in these conditions requires modelling approaches that reflect both local driving behaviour and temperature exposure.

Building on this foundation, the present study develops a region-adaptive simulation framework that integrates energy consumption, power demand and battery ageing mechanisms to analyse EV battery performance in Lagos. The purpose is to evaluate whether the commonly applied 70–80% SoH threshold is suitable for warm, congested urban environments and to estimate how performance evolves beyond this level. The findings aim to support EV cost optimisation, battery management strategies and policy planning in Nigeria and other West African cities with similar operating characteristics (Arrinda *et al.*, 2021; M. Etxandi-Santolaya *et al.*, 2024; Etxandi-Santolaya *et al.*, 2023).

Accordingly, this study addresses the following research questions:

1. Are the widely used 70–80% SoH end-of-life thresholds valid for lithium-ion batteries operating under warm, stop-and-go urban driving conditions typical of Lagos?
2. How does depth of discharge, road gradient, stop frequency, and ambient temperature interact to influence battery ageing in such environments?

3. Do functional indicators, such as daily driving range sufficiency or recharge frequency, offer a more accurate basis for determining battery end-of-life than capacity-based thresholds?

By answering these questions, the study provides evidence needed to adapt EV battery management strategies, extend practical battery life, and support policy decisions that reflect the realities of tropical urban systems. The subsequent sections present the literature review, modelling framework, simulation scenarios, results, and implications for EV deployment in emerging markets.

Literature Review

Lithium-ion batteries (LIBs) remain the preferred energy storage technology for electric vehicles (EVs) because of their high energy density, long cycle life and superior efficiency compared with lead-acid systems. Continued advancements in electrode materials, nanostructured composites and protective anode designs have improved conductivity and reduced structural instability, strengthening their suitability for modern EV applications (Afia *et al.*, 2024; Alashur, 2024; Asamoah *et al.*, 2024; Mikhaylik *et al.*, 2024). Despite these improvements, LIBs inevitably degrade due to electrochemical, thermal and mechanical processes (Rufino Júnior *et al.*, 2023). In several studies, two fundamental degradation pathways are identified: capacity fade and power fade; each shaped by complex interactions between battery chemistry, operating conditions and driving behaviour (Jang *et al.*, 2024; Mansir & Okonkwo, 2025; Martinez-Laserna *et al.*, 2018; Rufino Júnior *et al.*, 2023).

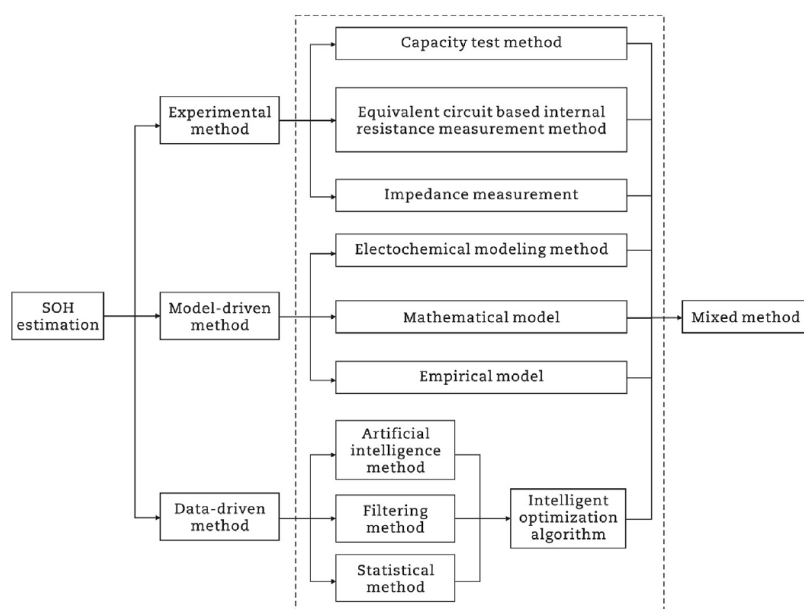


Figure 1: Methods of State of Health Estimation for Lithium-ion batteries (Liu *et al.*, 2023)

Capacity fade arises from loss of active materials, particle cracking, electrolyte decomposition and continuous solid–electrolyte interphase formation, which consumes cyclable lithium and reduces effective surface area (Duan *et al.*, 2023; Guo *et al.*, 2023; Kim *et al.*, 2023; Rufino Júnior *et al.*, 2023; Teel *et al.*, 2024). Power fade, in contrast, results from increases in internal resistance and cathode degradation, especially cracking under high voltage or heavy cycling, which restrict current delivery during high-load demands (Guo *et al.*, 2023; Martinez-Laserna *et al.*, 2018; Teel *et al.*, 2024). These degradation mechanisms are strongly influenced by depth of discharge, ambient temperature, cycle frequency, and charge rates, with harsh conditions accelerating the rate of decline (Duan *et al.*, 2023; Rufino Júnior *et al.*, 2023).

Because degradation arises from overlapping processes, accurate estimation of battery State of Health (SoH) has become central to EV battery research. Figure 1 presents the existing SoH-estimation techniques, which include empirical, model-based, data-driven, and hybrid approaches (Berecibar *et al.*, 2016; Ezemobi *et al.*, 2022; Li *et al.*, 2020; Liu *et al.*, 2023; Zhang *et al.*, 2022). Empirical techniques rely on observable degradation patterns and offer computational simplicity but limited precision (Ezemobi *et al.*, 2022). Model-based approaches, such as electrochemical and equivalent-circuit models, provide strong physical interpretability yet require substantial parameterisation. Data-driven methods leverage machine learning and large operational datasets to improve predictive capability (Berecibar *et al.*, 2016; Nuroldayeva *et al.*, 2023), while hybrid frameworks integrate physical principles with data-driven insight to improve real-time applicability (Nuroldayeva *et al.*, 2023). Still, many models fail to capture the combined influence of warm climates, shallow yet frequent cycling and region-specific congestion patterns typical of West African cities, resulting in limited accuracy under such conditions (Liu *et al.*, 2023).

Mathematical models play a particularly important role in forecasting battery ageing by capturing nonlinear relationships among temperature, cycle number, internal resistance, and capacity loss (Nuroldayeva *et al.*, 2023; Park *et al.*, 2020). Two principal SoH definitions, capacity-based and resistance-based, are widely employed (Braco *et al.*, 2022; Park *et al.*, 2020). Empirical formulations further distinguish between calendar ageing, influenced by temperature and resting state of charge, and cyclic ageing, governed by depth of discharge, current, and cycle count (Liu *et al.*, 2023). Although these frameworks are well-established, they rarely integrate the combined impacts of persistent warmth, high traffic density, and shallow but frequent cycles, conditions characteristic of urban Lagos.

Energy consumption modelling provides additional insight into how driving behaviour shapes battery use and degradation. As expected, urban EV operation is dominated by transient acceleration and deceleration, auxiliary loads and thermal effects, all of which significantly influence instantaneous power demand (Etxandi-Santolaya *et al.*, 2023; Lebeau *et al.*, 2015; Wu *et al.*, 2015). These driving patterns alter consumption profiles and increase shallow cycling, affecting thermal behaviour and accelerating specific ageing mechanisms (Etxandi-Santolaya *et al.*, 2023; Hao *et al.*, 2020). Energy consumption models

further explain that total EV energy usage comprises traction power, auxiliary demand and temperature-dependent battery performance (Lebeau *et al.*, 2015; Wu *et al.*, 2015). In congested environments, frequent acceleration and braking intensify transient power demands, causing degradation pathways that differ substantially from those seen in steady highway driving (Abousleiman & Rawashdeh, 2015; Etxandi-Santolaya *et al.*, 2023; Fiori *et al.*, 2016; Hao *et al.*, 2020).

A major focus of EV literature concerns how end-of-life should be defined. The widely accepted 70–80% SoH threshold originates largely from laboratory and cold-climate studies, where low temperatures sharply reduce available power and driving range (M. Etxandi-Santolaya *et al.*, 2024; Etxandi-Santolaya *et al.*, 2023; Plotz *et al.*, 2017; Saxena *et al.*, 2015). However, evidence increasingly shows that EVs operating in warm urban regions can remain functional well below these levels (Canals Casals *et al.*, 2022; M. Etxandi-Santolaya *et al.*, 2024). Short-trip, stop-and-go driving cycles may allow acceptable performance even at 60–65% SoH (Canals Casals *et al.*, 2022; Saxena *et al.*, 2015). Other studies emphasise that power capability, not nominal capacity, may be the more decisive factor determining later-life usability (Canals Casals *et al.*, 2022; M. Etxandi-Santolaya *et al.*, 2024; Etxandi-Santolaya *et al.*, 2023; Plotz *et al.*, 2017; Saxena *et al.*, 2015). Warm ambient conditions reduce cold-related losses, while urban traffic patterns introduce unique cycling behaviours that complicate conventional definitions of battery end-of-life (Arrinda *et al.*, 2021).

Extremely low temperatures impose some of the most severe constraints on lithium-ion battery performance, and the literature consistently shows that capacity loss becomes dramatic as thermal conditions move below freezing. At sub-zero temperatures, both maximum available capacity and discharge capability fall sharply because of intensified polarization, sluggish lithium-ion diffusion, and rising internal resistance (Chen *et al.*, 2024). For instance, at -10°C, only about 60.23% of the rated capacity can be utilized, and this drops to a mere 22% at -40°C (Lei *et al.*, 2014). These effects are not merely operational but deeply tied to ageing: prolonged exposure to cold accelerates irreversible lithium-inventory loss and resistance growth, producing a nonlinear decline in long-term battery health (Huang *et al.*, 2024). Such conditions define the technical boundaries that motivate thermal-management strategies and highlight the context-dependence of degradation behaviour.

Temperature variability further complicates these ageing dynamics, as both extreme cold and elevated heat amplify degradation through different pathways. High-temperature exposure increases the likelihood of rapid capacity fading, internal short circuits and accelerated side reactions (Paul *et al.*, 2023; Yang *et al.*, 2023). At the same time, low temperatures suppress discharge capacity and reduce efficiency. Charging conditions interact strongly with temperature: rapid charging at elevated temperatures heightens thermal gradients and exacerbates active-lithium loss, hastening capacity deterioration (Du

et al., 2023; Suresh *et al.*, 2024). Across these studies, a consistent conclusion emerges, maintaining operational temperatures within roughly 15–35 °C is crucial for protecting battery longevity and mitigating the compounding effects of thermal stress (Suresh *et al.*, 2024).

This broader evidence base also clarifies why the thermal environment of Lagos is particularly favourable for EV battery operation. Research identifies an optimal window of approximately 15–40 °C for lithium-ion batteries, with a more refined ideal range of 25–40 °C and minimal cell-to-cell temperature variance to prevent uneven ageing (Behi *et al.*, 2022; Dan *et al.*, 2021; Landini & O'Donovan, 2022). Chemistries commonly used in EVs, such as LiFePO₄, similarly achieve stable capacity and power delivery between 10–40 °C while avoiding the accelerated ageing that occurs at both thermal extremes (Sun *et al.*, 2014; Zang *et al.*, 2014). Lagos, with a consistently warm climate between 21 and 34 °C throughout the year (Spark, 2025), remains well within these optimal bands, meaning EV batteries in the region rarely experience low-temperature stress; the very conditions responsible for the most severe losses in capacity, power and long-term durability in the wider literature. Yet despite this advantageous thermal profile, little work has examined how such benign ambient temperatures interact with Lagos' distinct driving patterns, congestion levels and shallow cycling behaviour (Nwaigwe *et al.*, 2019; Ojo & Gbadegesin, 2024). This absence of region-specific modelling leaves a clear research gap: the need to quantify how Lagos' climate, combined with its urban traffic dynamics, shapes real-world ageing and the suitability of globally accepted end-of-life thresholds.

Methodology

This research adopts a simulation-based modelling approach to evaluate the functional end-of-life threshold of lithium-ion batteries in electric vehicles operating under Lagos urban driving conditions. The framework is implemented in MATLAB R2024b and simulates battery performance over a 30-year operational period. The model incorporates daily power demand estimation, energy consumption analysis, battery degradation mechanisms, and functional performance thresholds. The Tesla Model Y Long Range Rear-Wheel Drive is selected as the reference vehicle. Ambient temperature profiles reflect real-world climatic data for Lagos, while travel patterns simulate short to long commuting ranges typical in the city.

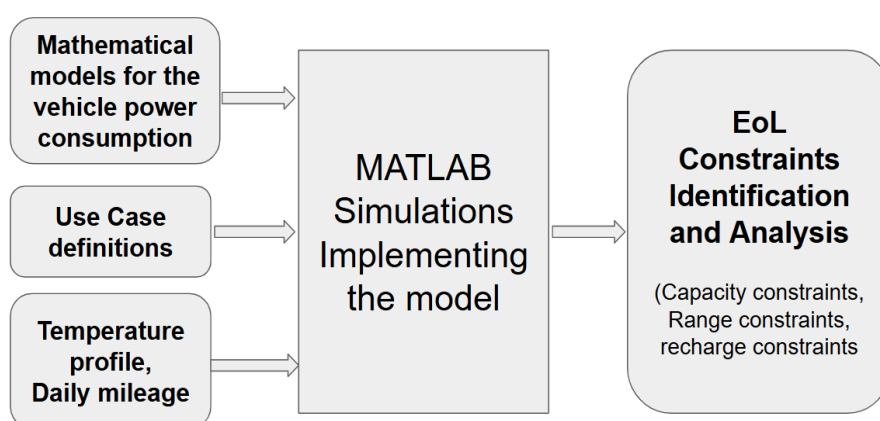


Figure 2: Methodology of implementation

Rationale for using Mathematical Modelling

Empirical testing of battery degradation under realistic conditions requires years of longitudinal data, which is often impractical due to time, cost, and instrumentation constraints, especially in Nigeria. A simulation-based methodology provides a scalable alternative, enabling the controlled manipulation of usage variables such as distance, depth of discharge, gradient, temperature, and stop frequency. This approach is consistent with previous studies that have explored region-specific performance and battery health in electric vehicles (Canals Casals *et al.*, 2022; Martinez-Laserna *et al.*, 2018). It can be adapted to various electric vehicle models, geographic regions, and operational contexts without the need for repeated physical experiments.

Research Framework and Approach

The structured approach adopted in the study to determine and analyse the EV battery degradation and end-of-life constraints is depicted in Figures 2 and 3. The research framework integrates vehicle dynamics, energy consumption modeling, battery degradation modeling, and end-of-life criteria analysis, all of which are implemented using MATLAB Software, version R2024b. The vehicle dynamics are shown in Figure 4.

Vehicle and Battery Parameter Initialization

The Tesla Model Y specifications used in this study were sourced from manufacturer documentation. Input parameters include the vehicle's mass, frontal area, drag coefficient, rolling resistance coefficient, and battery characteristics such as initial capacity, internal resistance, and warranty specifications as shown in Table 1. Ambient temperature data for Lagos were extracted from historical climate records, with maximum and minimum daily temperatures ranging between 23.6 °C and 31.0 °C (Spark, 2025). Daily travel distances are

generated using a Weibull distribution, informed by local commuting data. Table 1 presents the full parameter configuration.

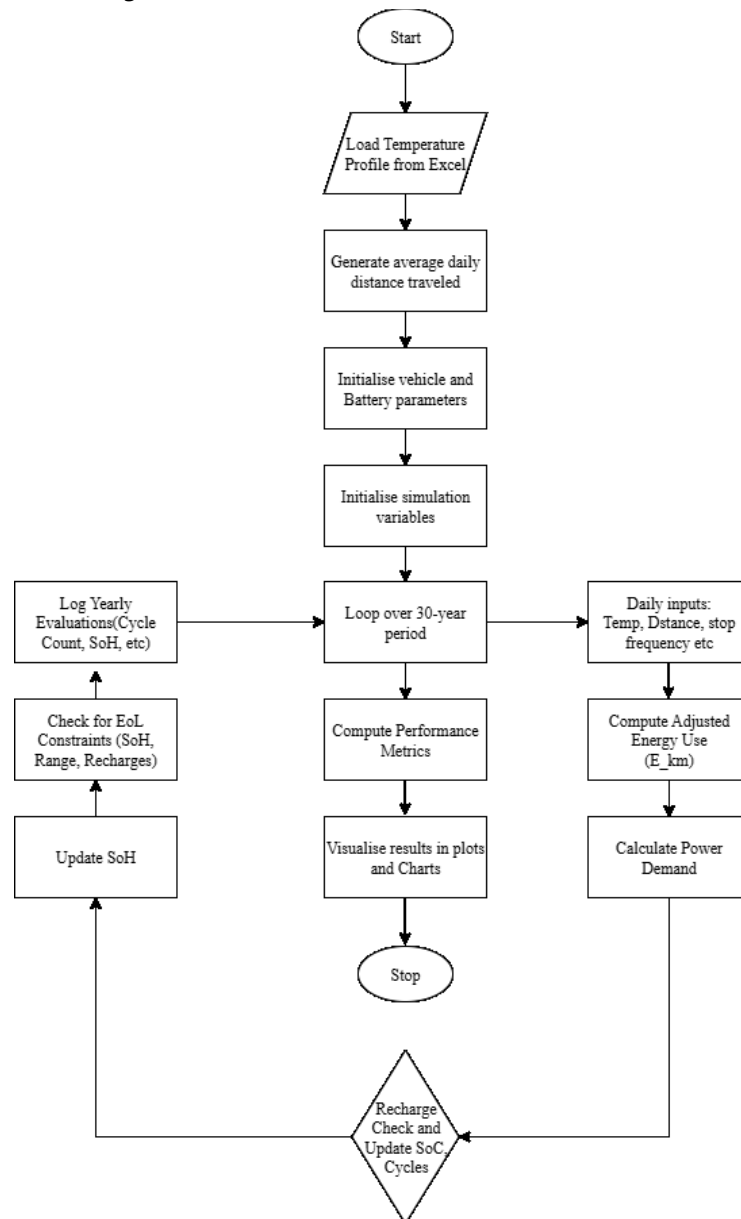


Figure 3: Simulation workflow for evaluating EV battery end-of-life in Lagos urban conditions.

Mathematical Models and Equations used

Power Consumption Modelling

The tractive power demand in Watt (W) was calculated using the fundamental vehicle dynamics model (Abousleiman & Rawashdeh, 2015; Fiori *et al.*, 2016; Wu *et al.*, 2015) :

$$P_{Demand} = \frac{1}{2} \rho A C_d v^3 + m g C_r v + m a v + m g \sin \theta v \quad (1)$$

Where v is the average speed (m/s) and θ is the road gradient (assumed 0 for flat terrain) Auxiliary power consumption, P_{aux} , for air conditioning was added when the ambient temperature exceeded 27 °C, operating at 2.5 kW for 50 percent of total travel time. The total power consumption per trip is therefore given as

$$P_{Total} = P_{Demand} + P_{aux} \quad (2)$$

3.4.2 Energy Consumption Model

The energy consumption per kilometer, influenced by the ambient temperature, road traffic, and the auxiliary power usage (Hao *et al.*, 2020), is given by equation (3).

$$E_{km,urban} = E_{km,ref} \times \left(1 + T_{coeff} \times (T_{Ambient} - T_{ref})\right) \times (1 + traf_{coeff} \times f_{stop-go}) \quad (3)$$

And the energy consumption per trip is given by

$$E_{trip} = E_{km,urban} \times D_{trip} \quad (4)$$

If the ambient temperature exceeds 27°C, auxiliary energy consumption from the air conditioning system is activated for 50% of the total driving time, calculated as given in equation (5).

$$E_{aux} = P_{aux} \times t_{aux} \quad (5)$$

$$t_{aux} = 0.5 \times \frac{D_{trip}}{v} \quad (6)$$

$$E_{total} = (E_{km,urban} \times D_{trip}) + E_{aux} \quad (7)$$

Equations (5–7) are derived from the relationships between the physical quantities: energy, power, velocity, distance, and time.

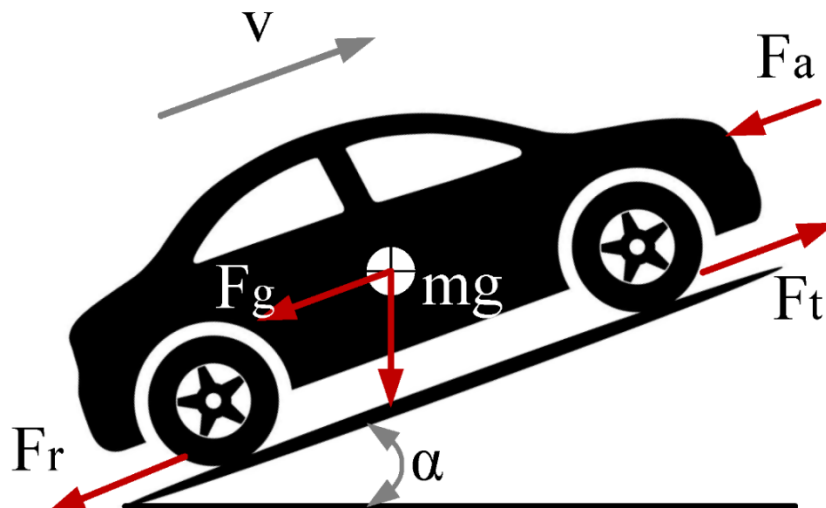


Figure 4: Vehicle dynamics that influence power consumption (Maite Etxandi-Santolaya *et al.*, 2024).

Battery Degradation Modelling

Degradation of the lithium-ion batteries, derived from the studies of Braco *et al.* (2022); Liu *et al.* (2023); Park *et al.* (2020), was modelled by integrating three principal mechanisms: cycle ageing, calendar ageing, and internal resistance growth. These mechanisms were implemented to simulate real-world performance losses over time, including the effects of daily usage patterns, ambient temperature, and power demands specific to Lagos urban conditions.

Cycle ageing represents capacity loss due to repetitive charging and discharging. The rate of degradation in this mode depends on the depth of discharge (DoD), the number of cycles, and the intensity of power draw. In the present model, degradation from cycling was formulated as a function of the square root of cumulative charge cycles and scaled by the operating DoD as given in (8).

$$\Delta SoH_{cycle} = k_1 \cdot DoD \cdot \sqrt{cycles} \quad (8)$$

Table 1: Tesla Y model and battery specifications (Author's Computation (2025)).

Parameter	Value	Unit	Source
Vehicle mass, m	1959	kg	(Tesla, 2025)
Frontal area, A	2.65	m ²	(Tesla, 2025)
Drag coefficient, C_d	0.23	-	(Tesla, 2025)
Rolling resistance coefficient, C_r	0.02	-	(Atamnia <i>et al.</i> , 2021)
Nominal battery voltage	340	V	(Tesla, 2025)
Initial battery capacity	60	kWh	(Tesla, 2025)
Full charge driving range	350	km	(Tesla, 2025)
Reference energy consumption	15.5/100	kWh/km	(Tesla, 2025)
Maximum power output	250	kW	(Tesla, 2025)
Maximum allowable current	734	A	(Tesla, 2025)
Air density, ρ	1.225	kg/m ³	Standard Atmospheric Conditions
Gravitational acceleration	9.81	m/s ²	Standard Gravitational Acceleration
Warranty mileage	160,000	km	(Tesla, 2025)
Warranty period	8	years	(Tesla, 2025)

Calendar ageing, which occurs even when the battery is not in active use, is primarily governed by ambient temperature and the state of charge (SoC) of the battery. This

degradation pathway was modelled using an Arrhenius-based exponential expression as given in equation (9).

$$\Delta SoH_{calendar} = k_3 \cdot e^{-\frac{E_a}{R(T_{ambient} + 273.15)}} \quad (9)$$

Where E_a is the activation energy (J/mol), R is the Universal gas constant (J/(molK)) and $T_{ambient}$ is the ambient temperature (°C) respectively.

The third degradation mechanism considered was power fade due to internal resistance growth. As batteries age, resistance increases within the cell, limiting the amount of usable power that can be drawn during operation. The available output power as given in (10) was therefore adjusted by subtracting resistive losses from the total power demand:

$$P_{available} = P_{Total} - I^2 R_{int} \quad (10)$$

Where R_{int} is the internal resistance and it increases as the battery degrades.

The final SoH update equation is then furnished in (11),

$$SoH(t) = SoH_0 - \Delta SoH_{cycle} - \Delta SoH_{calendar} - k_2 \cdot \left(\frac{I}{I_{max}}\right)^2 \quad (11)$$

End-of-life Criteria

The end-of-life of the electric vehicle battery is determined on three levels, and the conditions are expressed mathematically by equations (12)–(15).

- a. Traditional end-of-life threshold: When the state of health falls below the traditional 70% threshold.

$$SoH \leq 0.7 \quad (12)$$

- b. Functional-range end-of-life threshold: When the remaining capacity and full charge driving range can no longer support daily driving need

$$E_{total} > Q_{available} \quad (13)$$

$$Daily\ distance > Remaning\ Driving\ range \quad (14)$$

- c. When battery requires more than two recharges per day

$$Number\ of\ recharges > 2 \quad (15)$$

This multi-criteria definition allows the model to evaluate degradation not only from a theoretical standpoint but also in terms of real-world driving practicality.

Use Case Definitions and Environmental Data under Lagos Urban Conditions

The simulations were carried out across three different use cases, each defined by factors such as the vehicle's average daily travel distance, depth of discharge, and road gradient. These scenarios are outlined in Table 2. Each use case also corresponds to specific environmental conditions, which are detailed in Table 3. It is important to note, however, that the values used to define these use cases in Table 2 were not derived from empirical

data. Instead, they were developed based on informed judgement, drawing on practical experience and intuitive understanding of real-world driving behaviours in urban Lagos.

Scenarios for Simulation under Lagos Urban Driving Conditions

Twelve distinct simulation scenarios were designed to reflect a range of real-world driving conditions typical of urban life in Lagos, as detailed in Table 4. To capture the diversity in commuting habits across the city, three representative daily travel distances were selected: 15 km for short commutes, 30 km for medium-distance travel, and 40 km for longer daily journeys. These values were chosen to mirror common patterns among city drivers and provide a realistic basis for analysing battery performance under varied usage scenarios. The scenario-based design supports comparative evaluation of degradation rates, recharge frequency, and range limitations under different urban usage patterns. The simulation outcomes form the basis for proposing a context-sensitive redefinition of battery end-of-life thresholds suitable for electric mobility in urban Lagos.

Table 2: Use case definitions under urban Lagos conditions (Author's Computation (2025)).

Use case	Definition	Value
Average Daily Distance	Short	15 km
	Medium	30 km
	Long	40 km
Max DoD/Min SoC	Low	70%
	High	90%
Road Gradient	Flat	0°
	Random steepness	$1^\circ \leq \theta \leq 5^\circ$

Table 3: Environmental data for urban Lagos

Parameter	Definition	Value
Daily ambient Temperature	Maximum Average	31.00 °C
	Minimum Average	23.60 °C
	Reference Average	25 °C
Frequency of stops per km		5 – 15

Source: Spark (2025)

Table 4: Twelve scenarios of real-world driving under Lagos urban conditions Source: Author's Computation (2025)

Scenario	Daily Distance	Max DoD	Road Gradient	Stop Frequency (stops/km)
L1	Short (15 km)	Low (70%)	Flat (0°)	5-15
L2	Short (15 km)	Low (70%)	Random ($1^\circ \leq \theta \leq 5^\circ$)	5-15
L3	Short (15 km)	High (90%)	Flat (0°)	5-15
L4	Short (15 km)	High (90%)	Random ($1^\circ \leq \theta \leq 5^\circ$)	5-15
L5	Medium (30 km)	Low (70%)	Flat (0°)	5-15

Scenario	Daily Distance	Max DoD	Road Gradient	Stop Frequency (stops/km)
L6	Medium (30 km)	Low (70%)	Random ($1^\circ \leq \theta \leq 5^\circ$)	5-15
L7	Medium (30 km)	High (90%)	Flat (0°)	5-15
L8	Medium (30 km)	High (90%)	Random ($1^\circ \leq \theta \leq 5^\circ$)	5-15
L9	Long (40 km)	Low (70%)	Flat (0°)	5-15
L10	Long (40 km)	Low (70%)	Random ($1^\circ \leq \theta \leq 5^\circ$)	5-15
L11	Long (40 km)	High (90%)	Flat (0°)	5-15
L12	Long (40 km)	High (90%)	Random ($1^\circ \leq \theta \leq 5^\circ$)	5-15

Results and Discussion

This chapter presents the results obtained from the MATLAB simulations of the twelve scenarios and discusses their implications regarding the end-of-life threshold of electric vehicle (EV) lithium-ion batteries under the Lagos urban driving conditions. The results are analysed for different driving conditions and environmental factors. However, only the aggregated results for short-distance travelling, medium-distance travelling, and long-distance travelling are presented, analysed, and discussed in this chapter.

Use Case 1: Short-Distance Travel (15 km Daily)

In short-distance scenarios, the battery degraded slowly relative to other cases. The SoH remained above 84% by year 8 and dropped below 60% around year 15, falling to approximately 9% by year 25. The steepest degradation occurred between years 10 and 20, particularly under higher depth of discharge (DoD = 90%) and road gradients. Scenario 4 (DoD = 90%, gradient $> 0^\circ$) showed the most accelerated decline, indicating the detrimental effect of combining terrain stress with deep cycling. The remaining range mirrored this trend, falling from nearly 295 km in year 8 to below 35 km by year 25. However, the point of needing more than two daily recharges occurred around year 21, and range-based failure occurred near year 26.

These results suggest a practical EoL between 21 and 26 years, with a functional SoH of about 30%, shown in Table 5. Tables 5 - 7 present the aggregated results of the simulation for short-distance traveling and Figures 7 and 8 show the trends observed. Figures 5 and 6 show the trends observed for scenario 1 under short-distance traveling.

Table 5: State of Health (SoH) for short-distance traveling in urban Lagos

Year	Scenario 1 ($\theta=0$, DoD=70%)	Scenario 2 ($\theta>0$, DoD=70%)	Scenario 3 ($\theta=0$, DoD=90%)	Scenario 4 ($\theta>0$, DoD=90%)
8	84.27	84.28	82.87	82.58
10	77.83	77.94	75.88	75.62
15	58.15	58.20	54.97	54.92
20	33.59	33.74	30.48	30.58
25	9.73	9.62	8.47	8.35
30	3.81	3.33	3.74	3.29

Table 6: Remaining range (km) for short-distance traveling in urban Lagos

Year	Scenario 1 ($\theta=0$, DoD=70%)	Scenario 2 ($\theta>0$, DoD=70%)	Scenario 3 ($\theta=0$, DoD=90%)	Scenario 4 ($\theta>0$, DoD=90%)
8	294.96	294.99	290.12	289.11
10	272.42	272.81	265.62	264.68
15	203.61	203.70	192.45	192.26
20	117.68	118.08	106.71	107.02
25	34.06	33.66	29.64	29.26
30	13.32	11.67	13.08	11.50

Table 7: End-of-life summary for short-distance traveling in urban Lagos

Scenario	70% SoH Year	Functional EoL Year (Recharge > 2x Daily)	Functional EoL Year (Range Below Needs)
Scenario 1 ($\theta=0$, DoD=70%)	12.16	22.10	25.95
Scenario 2 ($\theta>0$, DoD=70%)	12.09	22.18	25.28
Scenario 3 ($\theta=0$, DoD=90%)	11.54	21.11	25.46
Scenario 4 ($\theta>0$, DoD=90%)	11.40	21.41	24.89

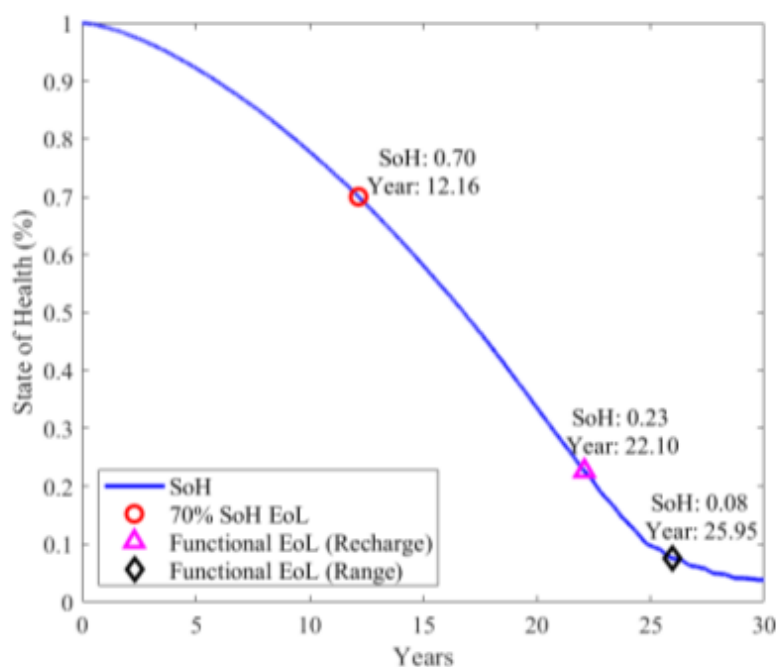


Figure 5: Plot of State-of-Health degradation for scenario 1

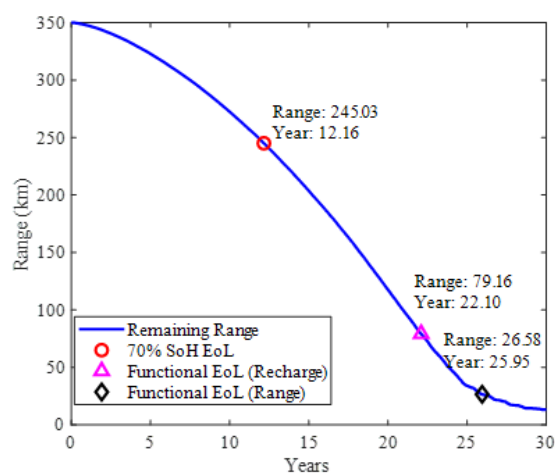


Figure 6: Plot of remaining driving range for scenario 1

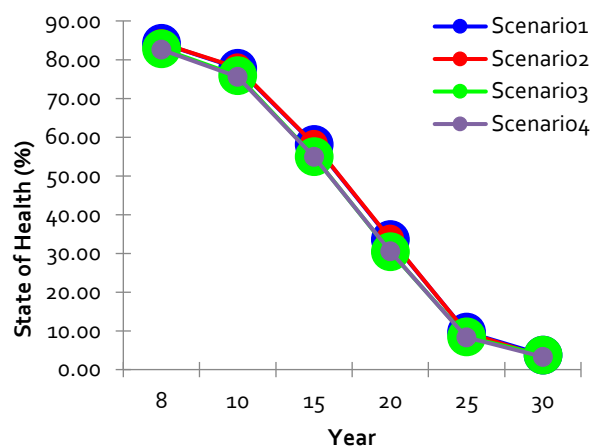


Figure 7: SoH degradation for use case 1 scenarios

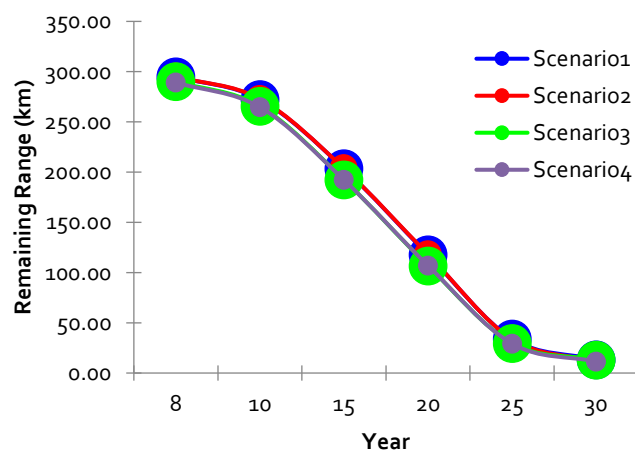


Figure 8: Remaining range for use case 1 scenarios

Use Case 2: Medium-Distance Travel (30 km Daily)

Medium-distance scenarios experienced faster degradation. In Tables 8 – 10, the aggregated results for this use case are presented. The battery crossed the 70% SoH threshold between 9.9 and 10.2 years and dropped below 50% by year 15, with SoH reaching only 6–10% by year 30. Increased DoD and road gradients amplified degradation, especially in Scenario 8 as shown in Figures 9 and 10.

Table 8: State of Health (SoH) for medium distance traveling in urban Lagos

Year	Scenario 5 ($\theta=0$, DoD=70%)	Scenario 6 ($\theta>0$, DoD=70%)	Scenario 7 ($\theta=0$, DoD=90%)	Scenario 8 ($\theta>0$, DoD=90%)
8	78.93	78.81	78.42	78.27
10	70.43	70.30	69.88	69.65
15	46.08	46.20	45.23	44.81
20	22.17	21.47	22.06	21.58
25	10.48	10.16	10.39	10.26
30	6.29	6.32	6.98	6.51

Table 9: Remaining range (km) for medium distance traveling in urban Lagos

Year	Scenario 5 ($\theta=0$, DoD=70%)	Scenario 6 ($\theta>0$, DoD=70%)	Scenario 7 ($\theta=0$, DoD=90%)	Scenario 8 ($\theta>0$, DoD=90%)
8	276.25	275.90	274.56	274.01
10	246.52	246.04	244.57	243.86
15	161.41	161.83	158.29	156.82
20	77.58	75.16	77.23	75.53
25	36.67	35.58	36.35	35.90
30	22.02	22.11	24.44	22.79

Table 10: End-of-life summary for medium distance traveling in urban Lagos

Scenario	70% SoH Year	Functional EoL Year (Recharge > 2x Daily)	Functional EoL Year (Range Below Needs)
Scenario 5 ($\theta=0$, DoD=70%)	10.12	15.21	22.09
Scenario 6 ($\theta>0$, DoD=70%)	10.12	15.12	22.15
Scenario 7 ($\theta=0$, DoD=90%)	9.98	15.41	21.95
Scenario 8 ($\theta>0$, DoD=90%)	9.96	13.40	21.23

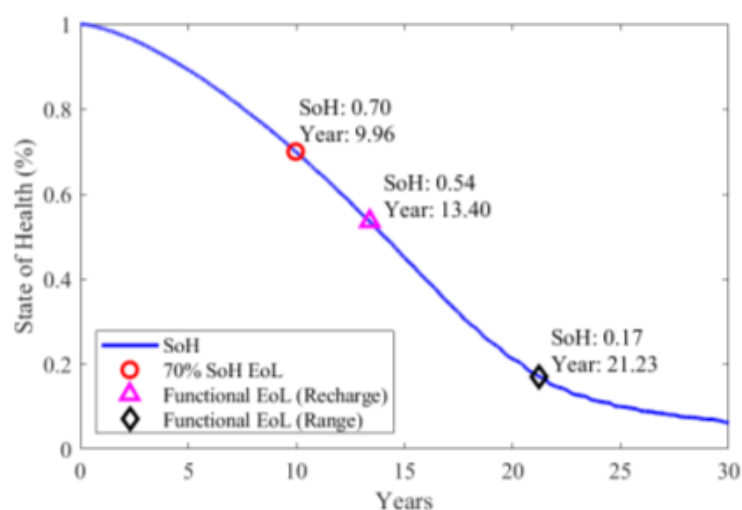


Figure 9: Plot of State-of-Health degradation for scenario 8

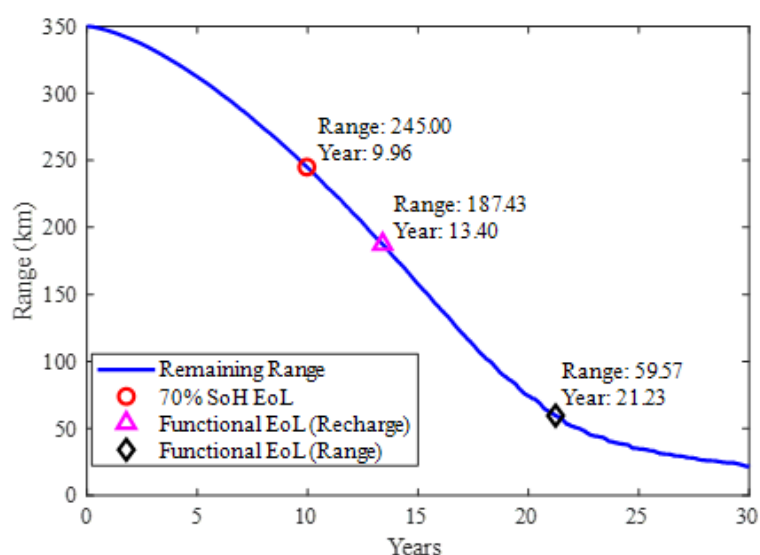


Figure 10: Plot of remaining driving range for scenario 8

Driving range declined from over 275 km to approximately 22 km by year 30. However, the practical limitations set in earlier: frequent recharging occurred between 13 and 16 years, and range-based limitations occurred between 21 and 23 years. These trends place the functional EoL around 12–20 years, with a practical SoH limit near 50%. This can be observed in Figures 11 and 12.

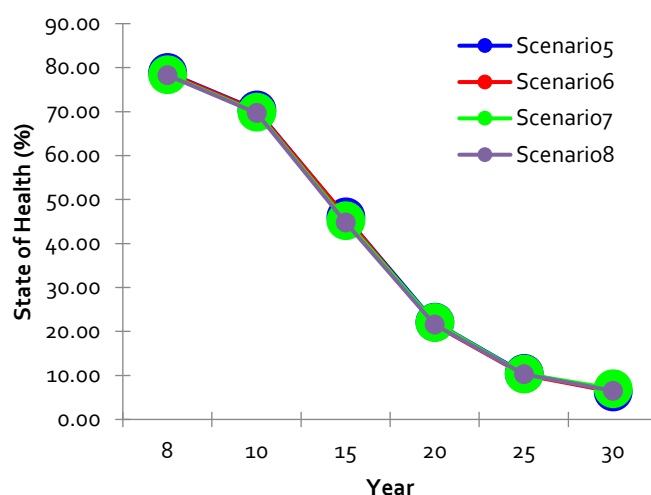


Figure 11: SoH degradation for use case 2 scenarios

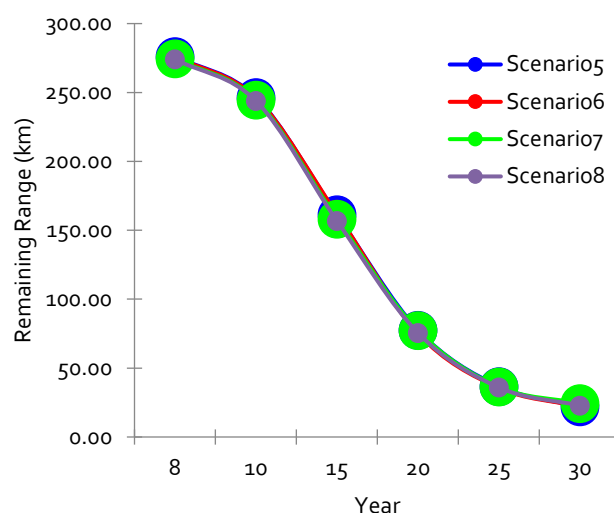


Figure 12: Remaining range for the use case 2 scenarios

Use Case 3: Long-Distance Travel (40 km Daily)

Long-distance driving led to the most rapid degradation. The 70% SoH threshold was reached between 9.6 and 9.7 years as shown in Table 11. By year 20, SoH had fallen below 25%, and by year 30, it dropped to about 9%. Interestingly, scenarios involving road gradients had slightly higher SoH at later stages due to energy distribution changes.

Table 11: State of Health (SoH) for long distance traveling in urban Lagos

Year	Scenario 9 ($\theta=0$, DoD=70%)	Scenario 10 ($\theta>0$, DoD=70%)	Scenario 11 ($\theta=0$, DoD=90%)	Scenario 12 ($\theta>0$, DoD=90%)
8	77.18	77.44	77.36	76.70
10	68.50	68.65	68.35	68.09

Year	Scenario 9 ($\theta=0$, DoD=70%)	Scenario 10 ($\theta>0$, DoD=70%)	Scenario 11 ($\theta=0$, DoD=90%)	Scenario 12 ($\theta>0$, DoD=90%)
15	43.99	43.64	43.48	43.73
20	23.34	24.05	23.01	22.62
25	13.39	13.85	12.78	13.03
30	9.30	8.99	8.92	8.77

Table 12: Remaining range (km) for long distance traveling in urban Lagos

Year	Scenario 9 ($\theta=0$, DoD=70%)	Scenario 10 ($\theta>0$, DoD=70%)	Scenario 11 ($\theta=0$, DoD=90%)	Scenario 12 ($\theta>0$, DoD=90%)
8	270.14	271.04	270.77	268.50
10	239.76	240.29	239.23	238.42
15	154.11	152.89	152.19	153.06
20	81.70	84.17	80.55	79.17
25	46.85	48.48	44.72	45.60
30	32.55	31.45	31.21	30.70

Table 13: End-of-life summary for long distance traveling in urban Lagos

Scenario	70% SoH Year	Functional EoL (Recharge > 2x Daily)	Year	Functional EoL Year (Range Below Needs)
Scenario 9 ($\theta=0$, DoD=70%)	9.67	12.05		21.18
Scenario 10 ($\theta>0$, DoD=70%)	9.67	7.85		20.78
Scenario 11 ($\theta=0$, DoD=90%)	9.65	9.10		20.59
Scenario 12 ($\theta>0$, DoD=90%)	9.54	11.87		19.59

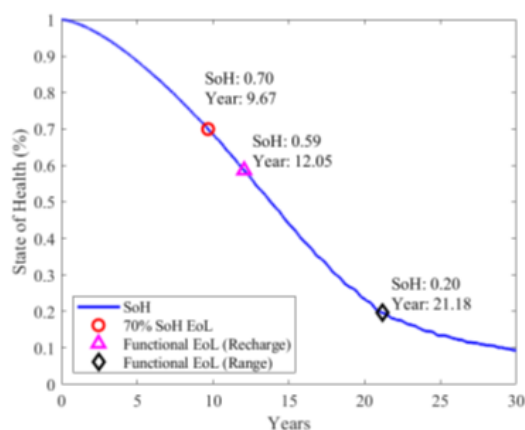


Figure 13: Plot of State-of-Health degradation for scenario 9

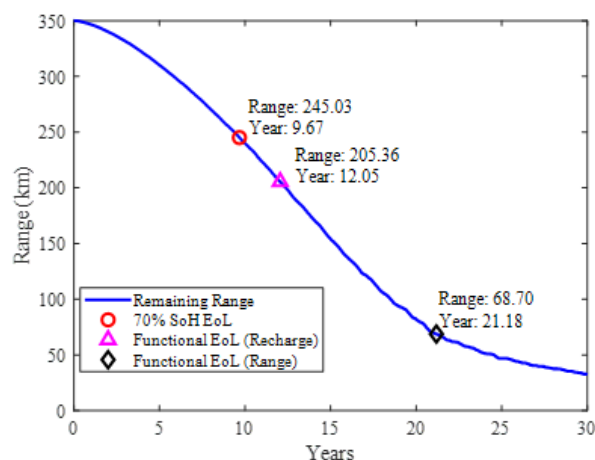


Figure 14: Plot of remaining driving range for scenario 9

Table 12 shows that the driving range dropped sharply from around 270 km at year 8 to under 33 km at year 30. Functional limitations emerged between years 10 and 16, with increased recharge frequency beginning near year 11 and practical range failure occurring by year 21. The functional EoL is therefore estimated between 10 and 16 years, with a corresponding SoH of approximately 55%. This is presented in Table 13 and the trends are observed in Figures 15 and 16. Figures 13 and 14 particularly shows the trend observed for scenario 9 under this use case.

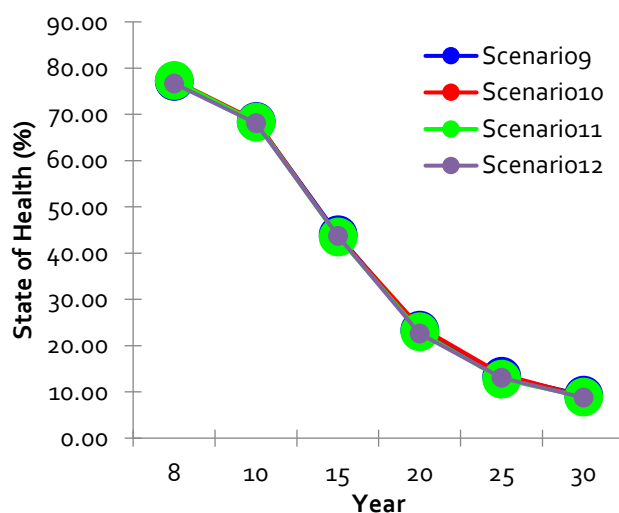


Figure 15: SoH degradation for use case 3 scenarios

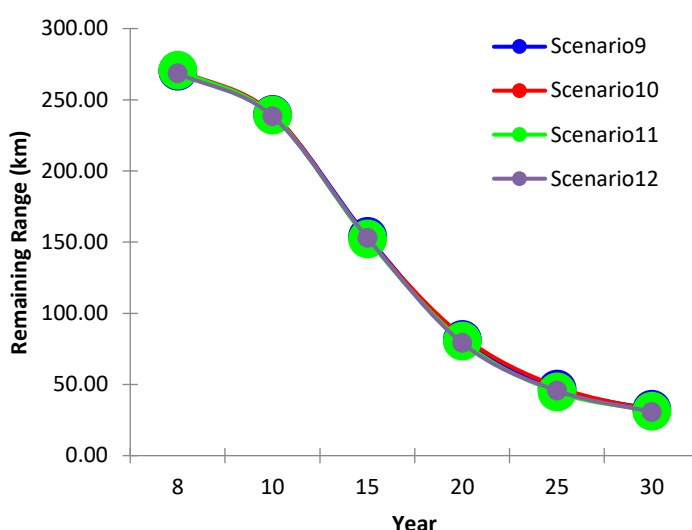


Figure 16: Remaining range for the use case 3 scenarios

Comparative Analysis Across Use Cases

A comparative analysis of the three use cases reveals distinct degradation patterns and are presented in Tables 14 – 16. Short-distance usage sustained higher SoH for longer periods and delayed EoL markers. Medium- and long-distance use cases, particularly under high DoD and road gradient conditions, exhibited earlier onset of functional limitations. Table 16 summarises EoL milestones across all categories. The conventional 70% SoH threshold was reached earliest in long-distance cases (9.65 years) and latest in short-distance scenarios (11.78 years). Recharge-based functional EoL occurred around year 10 for long-distance, year 14 for medium-distance, and year 21 for short-distance use. Range-based functional EoL was reached at year 20.8 for long-distance, year 22.1 for medium-distance, and year 25.7 for short-distance driving. These are shown in Figure 17 below.

On average, the functional EoL across all use cases occurred between 12 and 18 years, with an SoH range of 40–60%. These findings suggest that the conventional 70% SoH threshold is conservative and may not align with the actual functional end-of-life under Lagos urban driving conditions.

Table 14. Average State of Health (SoH) at specific years

Year	Use Case 1 (Short)	Use Case 2 (Medium)	Use Case 3	Average SoH (%)
8	83.64	78.63	77.16	79.81
10	76.61	70.26	68.32	71.73
15	56.79	45.83	43.48	48.70
20	31.93	22.97	23.23	26.04
25	9.45	9.39	12.49	10.44
30	3.46	6.54	8.52	6.17

Table 15: Average remaining range (km) at specific years

Year	Use Case 1 (Short)	Use Case 2 (Medium)	Use Case 3	Average range (km)
8	293.49	275.49	270.11	279.70
10	268.68	245.76	239.43	251.96
15	197.05	160.92	152.46	170.14
20	115.50	79.90	81.28	92.89
25	33.93	36.39	45.37	38.56
30	12.63	22.41	31.09	22.04

Table 16: End-of-life threshold summary

Scenario	70% SoH EoL Year	Functional EoL Year (Recharge > 2x Daily)	Functional EoL Year (Range Below Needs)
Use Case 1 (Short)	11.78	21.56	25.67
Use Case 2 (Medium)	10.03	14.42	22.12
Use Case 3 (Long)	9.65	10.22	20.82
Average	10.49	15.4	22.87

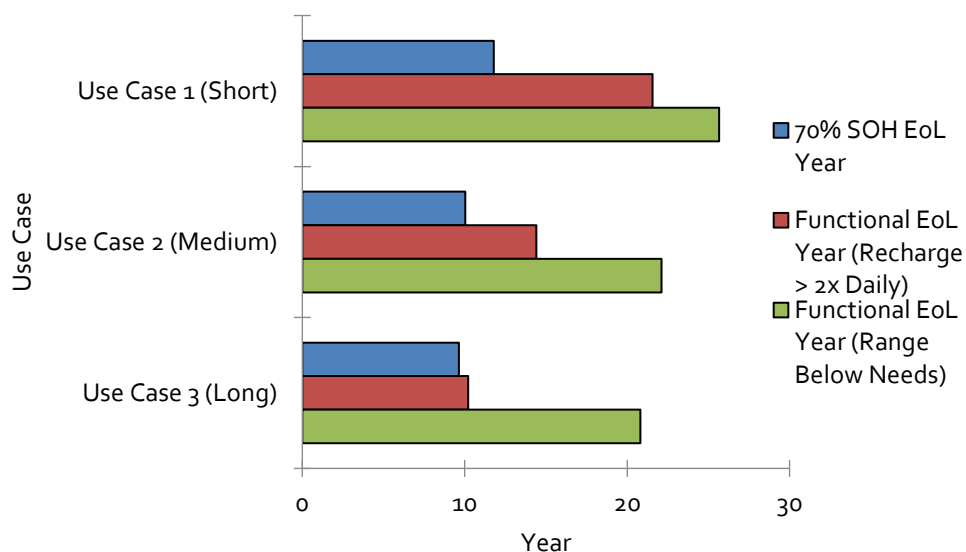


Figure 17: Comparison across use cases

Implications of Adopting a Functional End-of-Life Threshold for EVs in Urban Lagos

Adopting a functional end-of-life threshold significantly lowers the Total Cost of Ownership (TCO) for an EV driver in urban Lagos by extending the economically useful lifespan of the battery, the single most expensive component of the vehicle. For instance, the Tesla Model Y's retail price typically ranges between USD 48,000 and USD 60,000 depending on

configuration and market incentives, with the battery pack historically accounting for approximately 30–40% of that cost due to the high energy density and manufacturing complexity of large lithium-ion packs (BloombergNEF, 2023; Tesla, 2024).

Out-of-warranty replacement costs for a Model Y battery pack generally fall between USD 12,000 and USD 17,000, inclusive of parts and labour (Duniya, 2025; Recurrent, 2023). Under a conventional 70% State of Health (SoH) cutoff, many owners could be priced into premature replacement once a battery is viewed as degraded for warranty purposes (Duniya, 2025).

By contrast, a functional threshold of 40–60% SoH aligns the end of useful life with the actual point at which daily range and performance meaningfully degrade for urban Lagos conditions, which allows the battery to be used far longer before replacement (Saxena *et al.*, 2015). This extended use can conservatively delay a costly replacement by several years beyond the warranty year, thereby reducing depreciation and avoiding a potential replacement cost until truly necessary. Aligning EoL criteria with real-world performance rather than conservative warranty cut-offs therefore enhances the economic case for EV ownership in urban Lagos by lowering TCO and improving long-term asset utilisation.

Conclusion

From the analysis of the three use cases in urban Lagos, Nigeria, it is evident that the functional end-of-life threshold for electric vehicle lithium-ion batteries cannot be defined by the traditional 70–80% SoH threshold but must incorporate practical usability metrics. While the 70% SoH threshold is typically reached between 9.65 and 11.78 years, it does not immediately render the battery unusable. Instead, functional viability is more appropriately assessed by recharging frequency and remaining range. The point where vehicles require more than two full recharges daily occurs between 10.22 and 21.56 years, with an average of 15.4 years across all use cases. Similarly, the threshold at which the range drops below practical needs occurs between 20.82 and 25.67 years, with an average of 22.87 years. Therefore, the overall functional end-of-life threshold applicable to urban Lagos would be appropriately set at 40–60% SoH with a first life of approximately 12–18 years, extending the useful life of the battery for 4–10 years beyond the warranty year, thereby significantly reducing the total cost of ownership of EV in urban Lagos.

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