

Article

The Influence of Road Gradient Resistance on the Driving Range of Electric Vehicles

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Abstract

This study examines how longitudinal road gradients affect the energy consumption and driving range of a Tesla electric vehicle using dynamometer measurements and Simulink simulations. Tests performed on slopes from 0% to 4% show a strong inverse relationship between gradient and range, with more than a 62% reduction at a 4% incline. The Simulink model accurately reproduces these trends despite the tested vehicle's age and battery degradation. Shifting from driving range to energy consumption metrics provides a more robust assessment of vehicle efficiency, revealing that uphill segments substantially increase consumption, while downhill segments enable significant recuperation. When averaged, these effects nearly cancel out for moderate slopes, especially at higher speeds where aerodynamic drag dominates. Constant-speed simulations confirm that slope has minimal net impact at highway speeds but strongly affects consumption at urban speeds, with increases of up to 17% at a 4% gradient. Overall, the findings highlight road gradients as a key factor in EV energy modelling and emphasize the need to incorporate terrain and driving environment into predictive range estimation and eco-routing strategies.

Keywords: road gradient; simulation; electric vehicle range

1. Introduction

Advancements in technology, heightened environmental awareness, and supportive governmental policies have collectively accelerated the adoption of electric vehicles, both in personal transportation and in logistics operations [1]. Moreover, electric vehicles are gaining increasing prominence not only among the general public but also within the scope of contemporary scientific research [2].

1.1. Literature Survey on EV Range

The rapid transition toward sustainable mobility has placed electric vehicles (EVs) at the centre of research and development, driven by the dual goals of reducing greenhouse gas emissions and improving energy efficiency. EVs are studied both experimentally and through computational modelling, generating a rich body of literature that informs optimization strategies from battery management to drivetrain efficiency [3]. Among performance metrics, driving range is the most critical, shaping consumer acceptance and market penetration. Battery state of health (SOH) is especially important, as degradation reduces range over time, making monitoring methods indispensable [4].



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Real-world autonomy depends on multiple factors, such as vehicle mass, aerodynamics, battery characteristics, charging losses, environmental conditions and driving cycles [4–6]. Heavier vehicles and poor aerodynamics increase consumption, while operational variability complicates prediction. Fleet-level studies show that battery-electric buses have lower availability than diesel (76.9% vs. 85.5%), highlighting challenges in public transport [7]. Driving dynamics also matter: aggressive acceleration, high speeds, and frequent deceleration reduce range, while smoother driving extends it [8,9].

Discrepancies between expected and actual range have motivated predictive methodologies, from regression models to machine learning [10,11]. Regression offers interpretable relationships, while AI captures nonlinear dependencies. Data-driven approaches improve accuracy, especially when integrated into prognostic frameworks [11]. Beyond prediction, strategies such as thermal control, drivetrain optimization, and efficient HVAC use extend battery life and improve endurance [12]. Range estimation itself combines physical models based on motion and energy transfer with data-driven methods that identify correlations [11,13]. Integrating both yields robust predictions.

Environmental and operational factors—driving style, weather, traffic, and air conditioning—introduce variability, with HVAC use alone raising consumption by about 20% [14]. Simple test drives can estimate unknown loss parameters, though accuracy depends on controlling ambient conditions [15]. Improved SOC and range estimation methods now incorporate location-dependent and time-varying losses [16].

Autonomy continues to be a primary objective, yet present-day driving ranges still do not fully meet societal expectations for long-distance mobility [17]. Although improvements in battery technology have increased energy density and lowered costs, existing models address only portions of the problem; no comprehensive framework captures all variables influencing range prediction, highlighting the need for more integrated and holistic methodologies [18].

Temperature sensitivity remains a major issue: Low temperatures increase internal resistance, reducing discharge capacity [19]. HVAC systems consume disproportionately more energy in EVs, as they lack waste heat from combustion engines. Full cabin heating at -20°C can cut ranges by 60% [13], while high ambient temperatures reduce them by 13.4% in Tesla Model 3 [20]. Comparative studies of the Chevrolet Bolt, Nissan Leaf Plus and Tesla Model 3 show that climate control and battery temperature regulation can raise energy demand by over 50% [21].

Range anxiety remains a barrier, especially for long journeys where unpredictable factors complicate planning. Accurate estimation increases user confidence and supports operational efficiency. In logistics, high accuracy reduces costs by improving energy use, productivity, and route planning quality, ensuring optimal resource utilization [1,22,23].

1.2. Gradient Influence on Electric Vehicle Range: A Literature Review

Road gradient is one of the most influential external factors affecting the energy consumption and driving range of electric vehicles (EVs). Slope conditions alter instantaneous power demand, battery discharge rates, and regenerative braking efficiency. Approximately 26% of China's territory lies above 1000 m in altitude, with over 15 million vehicles operating in high-altitude areas, underscoring the relevance of gradient effects in real-world driving [24].

As gradient magnitude increases, acceleration and deceleration values rise, particularly during downhill travel, where extreme changes occur. These variations directly affect engine power and energy consumption [24], complicating range estimation. Standardized driving range calculations based on average fuel consumption rarely match real conditions, as drivers often experience lower ranges than estimated [25].

From a modelling perspective, incorporating gradient effects into trip-level energy consumption predictions has become increasingly important. Techniques such as differential voltage analysis, incremental capacity methods, and Kalman filter-based slope estimation enhance forecast accuracy [4,26]. Route-based prediction models that explicitly include gradient information show clear improvements in estimating vehicle range and energy use [27,28].

Reviews emphasize that the complexity of range prediction lies in the interplay of multiple factors, including vehicle dynamics, battery performance, auxiliary loads and topographical influences [18,19,29]. Physical models confirm that range is influenced by battery performance, auxiliary power demands, driving cycles, traffic density and road topology [30–32]. Among these, road gradient is particularly significant, as slope resistance directly increases traction power demand and accelerates battery depletion, while downhill driving enables energy recovery [33,34].

Energy demand rises sharply when slopes exceed 10° , and consumption can double on inclines greater than 15° [30]. Optimized regenerative braking technologies on steep slopes can recover 15–20% of energy otherwise lost [30].

Predictive energy-saving control (PEC) strategies require knowledge of upcoming gradients [34]. Neural network-based slope prediction methods, such as nonlinear autoregressive (NAR) models, have been tested successfully in real-time simulations, saving up to 6.35% of energy on uphill and flat roads at a time cost of 3% [34]. PEC strategies adjust vehicle speeds in anticipation of slope changes, reducing unnecessary braking and lowering aggregate energy consumption. Road inclination data can be obtained either from digital maps or slope estimation methods [34].

Simulation studies confirm that increasing grade reduces EV range. For example, a vehicle traveling 60 km on flat terrain saw its range reduced to 56.9 km on a 5% grade, with further reductions at higher grades [35]. Quantitative results show dramatic impacts: Increasing the slope angle from 0° to 4° reduced the range from 313.8 km to 86.11 km [23]. These findings highlight the necessity of slope-aware route planning and energy management.

Despite the extensive literature on individual factors, there remains a gap in integrating tractive effort, rolling resistance, aerodynamic drag and hill-climbing force into unified frameworks [36].

During downhill travel, regenerative braking torque is proportional to gradient magnitude. Larger gradients require higher torque, increasing the growth rate of battery SOC, while smaller gradients yield slower SOC recovery [37]. Hybrid energy storage systems (HESS) incorporate slope data into control algorithms to optimize EV driving range [38].

1.3. Methodologies for Studying the Role of Resistances in EV Range Estimation

1.3.1. Simulation Approach

Recent research has emphasized the role of artificial neural networks (ANNs), MATLAB/Simulink environments and advanced thermal management systems (TMSs) in developing predictive models with high fidelity and practical relevance. ANN-based computational models have been widely applied to estimate relationships between EV energy consumption and influencing factors such as slope angle, road topography, load, and wind speed [9,10,39]. For example, an EV model of Renault's Zoe was constructed in MATLAB/Simulink, incorporating longitudinal vehicle dynamics and the powertrain system. Mechanical power requirements were calculated using synthetic speed profiles and driving conditions, covering diverse slope angles, road conditions and environmental influences [39]. The dataset was designed to predict consumption by considering exogenous and endogenous parameters, including acceleration, initial speed, slope angle, additional

mass, wind speed and rolling resistance coefficient, with outputs defined as mechanical power at the wheels and equivalent electric power demand [39].

MATLAB/Simulink remains the most widely adopted simulation tool for EV modelling, enabling structured evaluation of vehicle mass, aerodynamics, driving cycles, SOC and environmental conditions [22,40]. SOC estimation has been a particular focus, with MATLAB simulations validating estimators of high accuracy, simplicity and robustness [41]. Extended Kalman filter (EKF) SOC estimators have demonstrated excellent robustness and accuracy across multiple driving cycles, with strong potential for real-time implementation in HEV/EV applications [42].

Numerical simulation based on mathematical modelling remains a general method for evaluating consumption on specific routes [43], while AMESim provides a library of components that can allow complex studies in most technical domains [44].

Simulation frameworks such as EleMA and INCEPTS have enabled high-fidelity analysis of gradient effects under variable topographical conditions [45,46]. INCEPTS integrates agent-based modelling with geospatial wind, elevation and temperature data, demonstrating up to a 30% variation in range due to environmental impacts [46].

The integration of ANN-based computational models [9,10,39], MATLAB/Simulink simulations [22,23,37,38,40–42] and advanced thermal management frameworks [20,21,47] provides a robust foundation for predicting EV energy consumption and range. Gradient effects remain central, influencing both propulsion demand and regenerative recovery, while SOC behaviour under standardized cycles offers critical benchmarks for performance evaluation. By combining physical modelling, AI-based estimators and thermal management strategies, future EV designs can achieve greater efficiency, reliability, and consumer confidence across diverse terrains and driving conditions.

1.3.2. Dynamometer-Based Methodology

Experimental research has been widely applied to evaluate the autonomy of electric vehicles (EVs) using standardized drive cycles. In [17], vehicle autonomy was studied on a dynamometer bench following the WLTC speed and load profile, highlighting how controlled laboratory conditions can reveal the evolution of range. Similarly, Ref. [5] tested a Kia e-Niro and VW e-Up! across several WLTC cycles, measuring drivetrain efficiency and charging losses with a specialized measuring box. These WLTC-based tests provide benchmarks for energy consumption and charging efficiency.

Chassis dynamometers are central to EV testing, enabling road load simulation under controlled conditions [9]. They allow researchers to emulate realistic driving scenarios, including slope, speed, load and passenger effects [2,48,49]. Studies confirm that road slope, dynamic loads and auxiliary heating or cooling significantly alter effective driving range compared to standard cycles [35,49,50].

Powertrain losses between battery and wheels—including inverter, motor, driveshafts, final drive and bearings—are measured on heavy-duty dynamometers across different velocities and torques [33]. While simulation software can support component selection, dynamometer testing remains essential to validate system combinations under diverse conditions [50,51]. Modern dynamometers often use auxiliary motors to emulate inertia or downhill slopes [38,41,50]. Paper [50] presents a methodology where the vehicle's own engine is used both to propel the vehicle and emulate gravitational and inertial forces, requiring inputs such as route topography, target speed and passenger load.

Battery modelling is also integrated into dynamometer studies. In [39], discharge characteristics at different temperatures were parameterized from experimental data or datasheets, while mapped motors and torque-control electronics reduced simulation time.

NEDC and EPA procedures similarly combine urban and extra-urban driving patterns indoors, though they lack wind and slope variability [22].

Recent work with a VW e-Up! mounted on a MAHA chassis dynamometer (MSR500) applied velocity profiles to generate realistic consumption and range data [52]. The results were compared with real-driving velocity profiles and onboard computer data, validating laboratory findings. To improve control accuracy under slow response and nonlinear conditions, in [53], fuzzy control, neural networks and adaptive predictive control were applied to chassis dynamometer algorithms.

1.3.3. On-Road Testing Method

Accurate measurement of energy losses in electric vehicles (EVs) requires methodologies that capture both battery-to-wheel energy flow and road load. A road-based measuring method presented in [15] provides direct insights into these losses under realistic driving conditions.

Significant discrepancies exist between the electric autonomy obtained in laboratory settings and that observed in real-world driving. Laboratory conditions are idealized, controlling variables such as slope, traffic and auxiliary loads, which cannot be fully replicated outside the test environment [8]. As a result, standardized approval cycles often fail to reflect actual energy consumption. The findings in [54] show that energy values obtained from cycles such as FTP72, FTP75, JC08, Japan10, NRDC and ECE-15 differ by 9.65–21.17% compared to real driving conditions. To improve accuracy, representative driving cycles tailored to specific cities or regions are recommended [13].

To ensure practical relevance, specifications used in simulations are aligned with commercially available EVs, allowing subsequent validation through experimentation on actual vehicles [35]. This approach bridges the gap between theoretical modelling and empirical performance, ensuring that predictive frameworks remain grounded in real-world data.

Overall, the literature emphasizes that while laboratory cycles provide controlled benchmarks, real-world conditions—particularly slope, load and auxiliary demands—must be incorporated into representative driving cycles and validated through experimental testing to achieve accurate estimates of EV energy consumption and autonomy.

1.4. Aim of the Work and Concluding Insights

Given the increasing adoption of EVs in diverse topographical regions, understanding the influence of road gradient resistance on driving range is not only a matter of technical optimization but also a prerequisite for reliable energy management and user confidence. These findings underline that reliable range prediction cannot be addressed by a single-variable approach; instead, it requires an integrated framework that considers both internal (battery health, vehicle mass, and auxiliary power consumption) and external (road gradient, traffic, and weather) factors. Also, it is highlighted that road gradients cannot be treated in isolation but rather as part of an integrated energy management framework that links vehicle dynamics, infrastructure and powertrain optimization.

Consequently, the influence of slope resistance must be analysed within this broader context of range-determining variables. Understanding the influence of slope resistance on EV autonomy is essential not only for vehicle-level design but also for fleet-level routing and charging strategies in future mobility systems.

This study aims to contribute to this growing body of knowledge by analysing the effects of road gradient on the autonomy of electric vehicles, building upon both experimental evidence and predictive modelling approaches presented in the literature. The

investigation is built around the WLTC measuring cycle, using the shortened Type 1 test procedure that incorporates two dynamic segments and two constant-speed segments.

A Tesla Model 3 was tested on a MAHA chassis dynamometer, where vehicle dynamics, road load coefficients and all required testing conditions were established to accurately reproduce real-world resistance. Dynamometer measurements were conducted for four ramp angles—0%, 2%, 3% and 4%—with the vehicle range defined by the number of cycles needed to discharge the battery from 80% to 10% state of charge. These tests revealed a strong inverse relationship between slope and range, with the vehicle's autonomy decreasing from 278.7 km on a flat surface to 104.76 km at a 4% incline, a reduction of more than 62%.

A detailed Simulink model was then developed and validated by reproducing the measured ranges for all slope values. Using this validated model, energy consumption was analysed across WLTC phases for both uphill and downhill driving. Additional simulations at constant speeds of 50 km/h and 130 km/h were performed to clarify the influence of road gradient by comparing uphill, downhill and averaged round-trip energy consumption across slopes from 1% to 4%. Together, these experimental and simulation results provide a comprehensive assessment of how road gradients shape electric vehicle energy demand and achievable driving ranges.

This study introduces several elements of novelty. First, the WLTC shortened Type 1 test procedure is applied to experimentally quantify the influence of longitudinal gradients under controlled and repeatable laboratory conditions. Second, a fully parameterizable Simulink model is developed, allowing adaptation to a wide range of electric-vehicle architectures, including single-axle traction or other constructive variations. Most importantly, this work provides a systematic analysis of energy consumption over shuttle-type routes, comparing outbound-and-return operations with horizontal travel. This bidirectional perspective captures compensatory effects that single-directional analyses cannot reveal, offering a more realistic representation of real-world driving.

To facilitate the understanding of this paper, a concise overview of the sections that structure the methodological development of this study is provided.

Section 2 introduces the WLTC-derived shortened Type 1 driving cycle used as the reference velocity profile, followed by a detailed description of the selected test vehicle and the complete chassis-dynamometer configuration. This section also describes the numerical framework developed in Simulink, including the implementation of the electric vehicle model, the battery representation and the integration of slope-dependent velocity profiles.

Section 3 reports the results obtained from both the experimental measurements and the simulation environment. The dynamometer tests yield the measured driving ranges for four distinct slope values, while the simulation results encompass model validation, WLTC-phase energy consumption analysis and additional constant-speed evaluations.

Section 4 synthesizes the findings derived from the experimental and numerical analyses, highlighting areas of agreement, sources of deviation and the physical mechanisms underlying the observed trends.

Section 5 presents a summary of the principal contributions of this study and a discussion of potential avenues for future research aimed at enhancing the accuracy and applicability of electric vehicle range prediction under varying road-gradient conditions.

2. Materials and Methods

In this section, the chosen velocity profiles are described, together with the test vehicle and the complete measurement configuration. A comprehensive explanation of the measurement procedure is included, followed by an analysis of energy consumption in different cases.

2.1. WLTC Measuring Cycle

Vehicle emission testing is typically conducted in a controlled laboratory setting, with real-world driving conditions emulated through a chassis dynamometer programmed to reproduce standardized driving cycles.

The World Harmonized Light-Duty Vehicles Test Procedure (WLTP) is a globally harmonized standard for determining levels of pollutants, and it is also used to determine the range of electric vehicles. The WLTP CLASS 3b cycle, which corresponds to the vehicle of interest, is used for vehicles with a power mass rate (PMR) greater than 34 W/kg and a maximum speed exceeding 120 km/h. The cycle comprises four sections—low, medium, high, and extra high—as depicted in Figure 1 with data from [55]. The complete cycle has a duration of 1800 s, during which the vehicle covers 23.262 km and reaches a maximum velocity of 131.3 km/h.

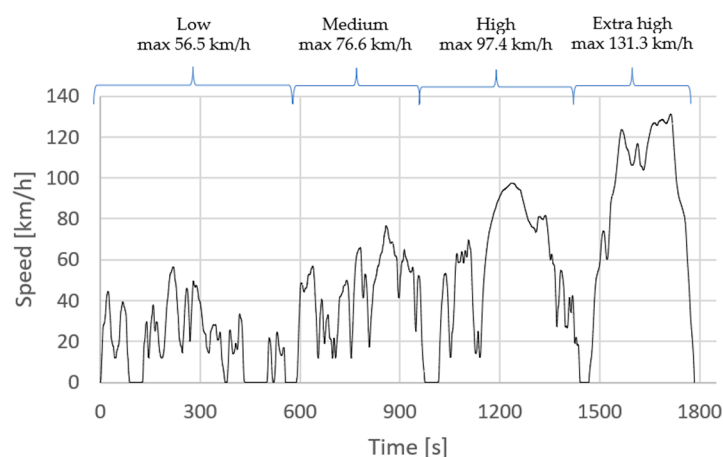


Figure 1. Worldwide Harmonized Light Vehicles Test Procedure 3B for determining energy consumption for light-duty electric vehicles with a power-to-weight ratio greater than 34 W/kg (WLTP CLASS 3B driving cycle).

Figure 2, with data from [5], illustrates the vehicle speed across the WLTC sections—“low”, “medium”, “high” and “extra high”—plotted as a function of distance travelled. Representing speed against distance aligns directly with the conventional consumption metrics for BEVs, which are typically expressed in Wh/km or kWh/100 km, with both referring to distance covered.

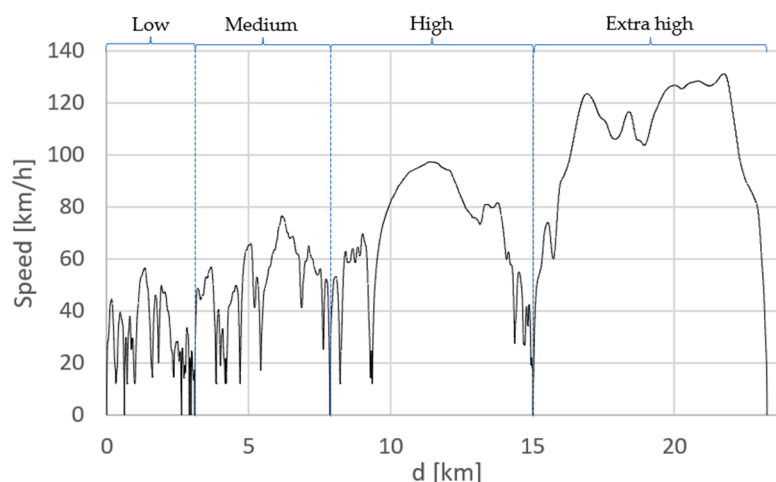


Figure 2. WLTC speed profile v as a function of the distance driven d .

In none of the WLTC sections does the vehicle cover more than 10 km. The combined distance share of the “low” and “medium” sections is 33.7%, which is comparable to that of the “high” and “extra high” sections. In terms of time distribution, the majority is spent in the “low” section, while the “medium” and “high” sections each account for roughly one quarter. The “extra high” section contributes slightly less, at just under 18% of the total time [5].

In this paper, the shortened Type 1 test procedure [56] is used, which can include two dynamic segments (DS₁ and DS₂) combined with two constant-speed segments (CSS_M and CSS_E). The cycle used for the measurements corresponds to the one shown in Figure 3, as it appears in the settings menu of the Horiba Stars VETS 2.5 chassis dynamometer software. This software was used on the equipment of the Romanian Auto Registry (RAR) in Bucharest, Romania.

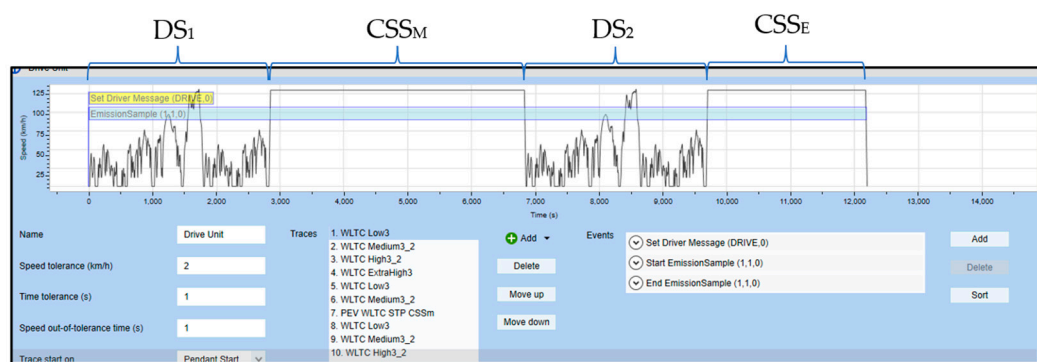


Figure 3. Vehicle speed trace of the shortened Type 1 test procedure, obtained as a screenshot from the Horiba Stars VETS 2.5 chassis dynamometer software.

Within the WLTP framework, the dynamic segments DS₁ and DS₂ are specifically utilized to quantify the energy consumption profile of the vehicle under representative driving conditions. These segments replicate transient load variations and speed fluctuations, thereby enabling a robust assessment of the vehicle’s efficiency across the applicable cycle. In contrast, the constant-speed segments CSS_M and CSS_E are incorporated to accelerate the depletion of the rechargeable energy storage system (REESS). By maintaining fixed operating points, these segments shorten the overall test duration relative to the conventional consecutive Type 1 cycle procedure, while still ensuring that the discharge characteristics of the REESS are captured in a controlled and repeatable manner.

2.2. Assessed Electric Vehicle

The vehicle selected for this work is a Tesla 3, a model that represented one of the top three best-selling EVs in the United States for the calendar year 2019 [21].

The tested model is 003 E3D (E3 = long-range battery; D = dual motor (AWD); B = base motor (3D5 rear)). The main technical specifications of the considered electric vehicle are summarized in Table 1.

Table 1. Electric vehicle technical specifications extrapolated from technical specifications of TESLA 3 model [20,51,56–59] (Dual Motor Standard, Model 2020).

Parameter	Value
Curb weight	1931 kg
Test weight	2047 kg
Rolling friction coefficient	0.010
Drag coefficient	0.23
Frontal area	2.22

Table 1. *Cont.*

Parameter	Value
Transmission gear ratio	9
Maximum vehicle design speed	233 km/h
Tire width	235 mm
Tire aspect ratio	45
Rim diameter	18 inch
Free wheel radius	334.35 mm
Front motor type	3D3 Asynchronous Motor (ACIM)
Front motor power	158 kW
Front motor torque	275 Nm @ 0–6380 rpm
Front motor voltage	335 V
Rear motor type	3D5 Permanent Magnet Synchronous Motor (PMSM)
Rear motor power	208 kW
Rear motor torque	420 Nm @ 0–6000 rpm
Rear motor voltage	335 V
Total power	366 kW
Total torque	493 Nm
Battery type	NCA (Lithium Nickel Cobalt Aluminium Oxide)
Battery model	NCR21700A
Battery pack	4416 cells, 96s46p, 4 modules
Battery nominal capacity	77.8 kWh
Battery nominal voltage	360 V
Battery energy density	260 Wh/kg

2.3. Measurement Setup on the Chassis Dynamometer

The electric vehicle was mounted on a MAHA chassis dynamometer using clamps and fastening components, as shown in Figure 4. The installation followed EU procedures and the dynamometer's operating manual. The equipment is under the authority of the Romanian Auto Registry (Registrul Auto Român) in Bucharest, Romania.

**Figure 4.** Test setup and road load simulation test of the EV on the chassis dynamometer.

The data presented in Table 1 is also utilized by the dynamometer control to simulate inertia and aerodynamic drag losses.

Experimental research was conducted by operating the vehicle on a chassis dynamometer in accordance with the shortened Type 1 test procedure and load profile. Before the commencement of each test, the vehicle's battery was charged to 80% state of charge (SOC) and subsequently preconditioned, being maintained at a controlled temperature for approximately 12 h. The investigation focused primarily on multi-cycle full depletion tests performed at an ambient temperature of 22 °C. For the modelled test method, four distinct measurement setups were employed. The first setup enabled data acquisition during the execution of velocity profiles on the dynamometer. The shortened Type 1 test was repeated until 10% SOC.

2.3.1. Vehicle Dynamics

The motion of a vehicle on the road is governed by the road load, which consists of rolling resistance F_r , aerodynamic drag force F_{air} , road slope force F_g and acceleration force F_i . The longitudinal dynamics of the vehicle can be expressed as follows [22]:

$$F_x = F_r + F_{air} + F_g + F_i = f_r \cdot m \cdot g + 1/2 \cdot \rho \cdot C_d \cdot A \cdot (v - w)^2 + m \cdot g \cdot \sin \alpha + m_{eff} \cdot a_x, \quad (1)$$

where

- F_x is the propelling force, N;
- F_r is the rolling resistance force, N;
- F_{air} is the air dynamic drag force, N;
- F_g is the gravity force, N;
- F_i is the acceleration force caused by vehicle inertia, N;
- f_r is the rolling resistance coefficient;
- m is the vehicle mass, kg;
- g is the gravitational acceleration, m/s^2 ;
- ρ is the air density, kg/m^3 ;
- C_d is the aerodynamic drag coefficient;
- A is the vehicle frontal area, m^2 ;
- v is the vehicle speed, m/s ;
- w is the wind speed in the vehicle driving direction, m/s ;
- α is the road slope, °;
- m_{eff} is the vehicle effective mass, kg;
- a_x is the vehicle acceleration, m/s^2 .

The effective mass m_{eff} accounts for both the vehicle mass and the equivalent inertia of the motor and wheels:

$$m_{eff} = m + 4 \cdot J_w / R_e^2 + J_{em} / r_d^2 \cdot R_e^2, \quad (2)$$

where the following are defined:

- J_w is the wheel inertia, $kg \cdot m^2$;
- J_{em} is the motor inertia, $kg \cdot m^2$;
- R_e is the effective rolling radius of the tire, m;
- r_d is the gear reduction ratio.

The required electric motor power of the vehicle is computed as the sum of individual power demands necessary to overcome various resistances and road loads. Accordingly, the electric motor power is expressed as follows:

$$P_{EM} = P_r + P_{air} + P_g + P_i, \quad (3)$$

where

- P_r is the rolling resistance power, W;
- P_{air} is the aerodynamic drag power, W;
- P_g is the gravitational power due to road slope, W;
- P_i is the power to overcome inertial forces, W.

When $P_{EM} > 0$, the propulsion system operates in driving mode. Conversely, when $P_{EM} < 0$, the system functions in regenerative mode. Regenerative power, as presented in [20], is therefore expressed as follows:

$$P_{regen} = \min(P_{EM}, 0) = \min(P_i + P_r + P_{air} + P_g, 0), \quad (4)$$

When vehicles are tested on chassis dynamometers, the calculation of energy demand is based on the target speed trace given in discrete time sample points. For the calculation, each time sample point is interpreted as a period of 1 s. The total energy demand E for the whole cycle is calculated by summing E_i over the corresponding cycle time between t_{start} and t_{end} according to the equation from [56]:

$$E = \sum_{t_{start}}^{t_{end}} E_i, \quad (5)$$

where

- $E_i = F_i \cdot d_i$ if $F_i > 0$;
- $E_i = 0$ if $F_i \leq 0$.

Moreover,

- t_{start} is the time at which the applicable test cycle or phase starts, s;
- t_{end} is the time at which the applicable test cycle or phase ends, s;
- E_i is the energy demand during time period $(i - 1)$ to (i) , W·s;
- F_i is the driving force during time period $(i - 1)$ to (i) , N;
- d_i is the distance travelled during time period $(i - 1)$ to (i) , m.

The driving force needed to compute the energy demand is expressed as follows:

$$F_i = f_0 + f_1 \cdot \left(\frac{v_i + v_{i-1}}{2} \right) + f_2 \cdot \frac{(v_i + v_{i-1})^2}{4} + (1.03 \cdot TM) \cdot a_i, \quad (6)$$

where

- F_i is the driving force during time period $(i - 1)$ to (i) , N;
- v_i is the target speed at time t_i , km/h;
- TM is the test mass, kg;
- a_i is the acceleration during time period $(i - 1)$ to (i) , m/s²;
- f_0 , f_1 , and f_2 are the road load coefficients for the test vehicle under consideration (TML, TMH, or TM_{nom}) in N, N/km/h, and in N/(km/h)², respectively.

$$a_i = \frac{v_i - v_{i-1}}{3.6 \cdot (t_i - t_{i-1})}, \quad (7)$$

Here, the following are defined:

- v_i : Target speed at time t_i , km/h;
- t_i : Time, s.

The distance travelled needed to compute the energy demand in (5) is expressed as follows:

$$d_i = \left(\frac{v_i + v_{i-1}}{2} \cdot 3.6 \right) \cdot (t_i - t_{i-1}), \quad (8)$$

where

- d_i is the distance travelled in period $(i - 1)$ to (i) , m;
- v_i is the target speed at time t_i , km/h;
- t_i is time, s.

2.3.2. Road Load Coefficient Determination for Dynamometer Simulation

Dyno coefficients are established to replicate real-world driving conditions. These coefficients account for the inertia of the rollers, rolling resistance, aerodynamic drag and mechanical losses. The process typically involves a coast-down test, in which the vehicle is allowed to decelerate freely on the dynamometer; from this deceleration, resistance parameters are calculated. The software then applies correction factors to transform the measured force at the rollers into engine torque and power values [56]. In practice, this means that dynamometer results represent wheel torque and power, which are subsequently corrected to approximate engine output. The accuracy of these coefficients is crucial, as they ensure that laboratory measurements reflect the vehicle's real-world performance.

The manufacturer must ensure the accuracy of the road load coefficients for every production vehicle within the designated road load family [56]. According to the EC Type-Approval certificate of the tested vehicle [59], the road load coefficients are $f_0 = 183.0$ N, $f_1 = 0.432$ N/(km/h), and $f_2 = 0.02734$ N/(km/h)², as illustrated in Figure 5.

Results: version: <u>E3DBb1#</u>	Interpolation family identifier: <u>IP-09 1857-5YJ-1</u>		
	VH	VM (if applicable)	VL (if applicable)
Electric Consumption (Combined) (Wh/km)	160	--	--
Pure Electric Range (Combined) (km)	560	--	--
Pure Electric Range (City) (km)	682	--	--
f_0 (N)	183.0	--	--
f_1 (N/(km/h))	0.432	--	--
f_2 (N/((km/h) ²))	0.02734	--	--
RR	7.43	--	--
Delta Cd*A (for VL if applicable compared to VH) (m ²)	N/A	--	--
Test mass (kg)	2047	--	--

Figure 5. Road load coefficients specified in the EC Type-Approval certificate of the tested vehicle [59].

VH the figure above refers to the test of the vehicle producing the higher, and preferably the highest, cycle energy demand of the interpolation family, and VL refers to the one producing the lower, and preferably the lowest, cycle energy demand of that selection, as specified in [56].

An image of the dynamometer software interface used during testing is presented in Figure 6, displaying the road load coefficients.

The dyno coefficients used were obtained from the dynamometer coast-down test conducted for adaptation, and their values are $f_0 = -8.57$ N, $f_1 = 0.4542$ N/(km/h) and $f_2 = 0.02408$ N/(km/h)². These coefficients were entered in the control PC of the chassis dynamometer.

A test driver operated the vehicle on the chassis dynamometer, following the speed profile of the velocity profile. In Figure 7, only a segment of the test period is displayed, demonstrating that the test profile was followed.

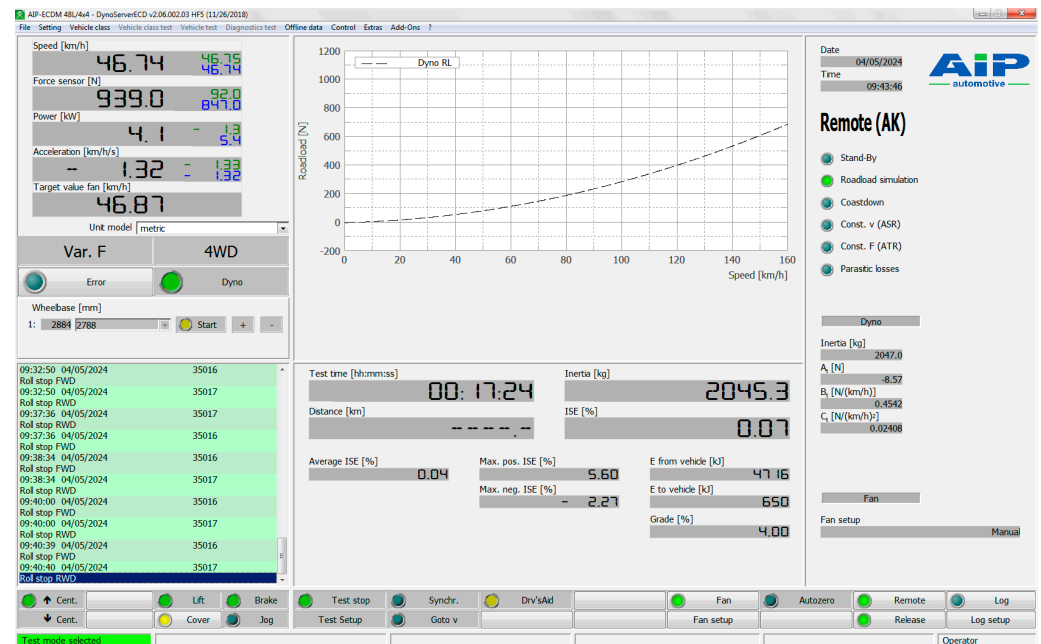


Figure 6. Interface of the dynamometer software used during testing.

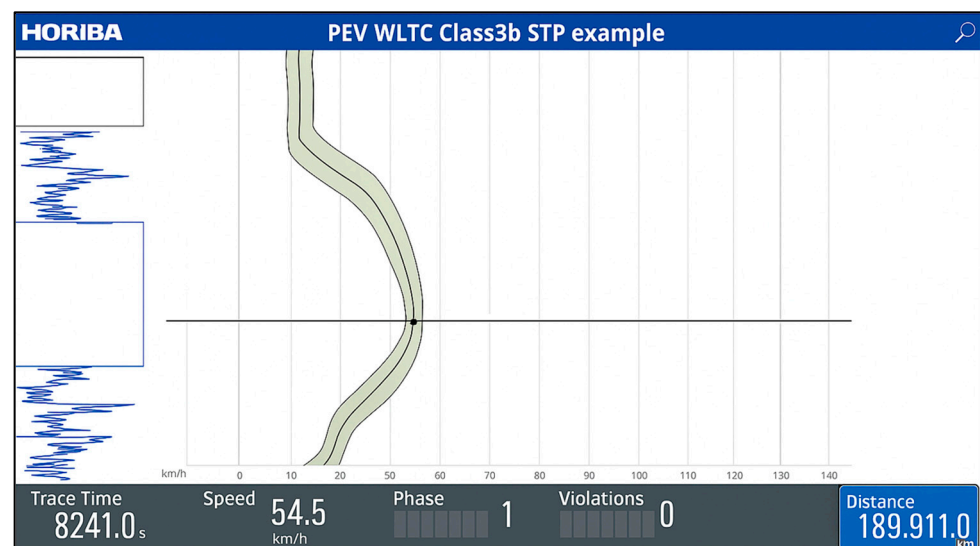


Figure 7. Dynamometer software interface used in testing, displaying a portion of the WLTC derived shortened Type 1 driving cycle: The blue curve on the left represents the entire cycle, while the one in the center shows only the portion captured during the measurement.

2.3.3. Testing Conditions for Dynamometer Simulation

During the entire experimental period, the test of the vehicle under study was conducted under conditions that met the prescribed temperature requirements, with values maintained at approximately 23 °C.

Airspeed simulation was carried out using high-capacity blowers driven by electric motors. The blowers enabled the propulsion of air in the direction of the test vehicle. For the experimental investigations presented in this study, the blower system was programmed to operate in automatic mode, reproducing the vehicle's speed profile as prescribed by the standardized application procedure of the testing method.

2.4. Simulink Simulation

In this part of the study, the mathematical model of an electric vehicle (EV) is implemented in the MATLAB/Simulink 2022b environment to enable scenario-based simulations. These simulations were conducted to systematically evaluate the influence of key parameters on the vehicle's driving range. To identify the range, the vehicle model proposed in [47] was optimised and used as represented in Figure 8.

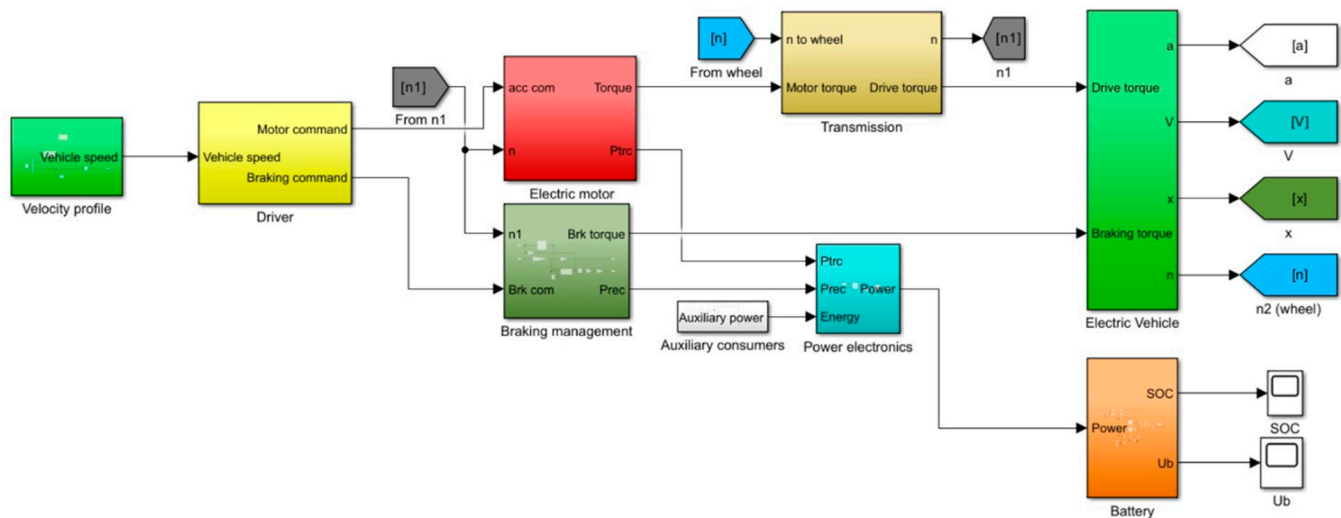


Figure 8. Tesla 3 model in MATLAB/Simulink 2022b.

The dynamic model evaluates the traction force generated by the mechanical drive and calculates both the load torque at the motor shaft (M_e^*) and the corresponding shaft speed. The AC motor model determines the electrical power (P_{me}^*) required, which must be supplied by the inverter. Finally, the converter model estimates the power delivered at the terminals of the battery pack [55]. The objective of this work was to develop and validate an energy-study model capable of providing accurate calculations across the full battery state-of-charge range and for typical road gradients.

The following figure illustrates the electric motor diagram that was implemented within the modelling program.

Figure 9 illustrates the torque curves of the Tesla Model 3 (2020). The underlying data were taken from Tesla Motors' official specifications and EVSpecifications [51,57–59].

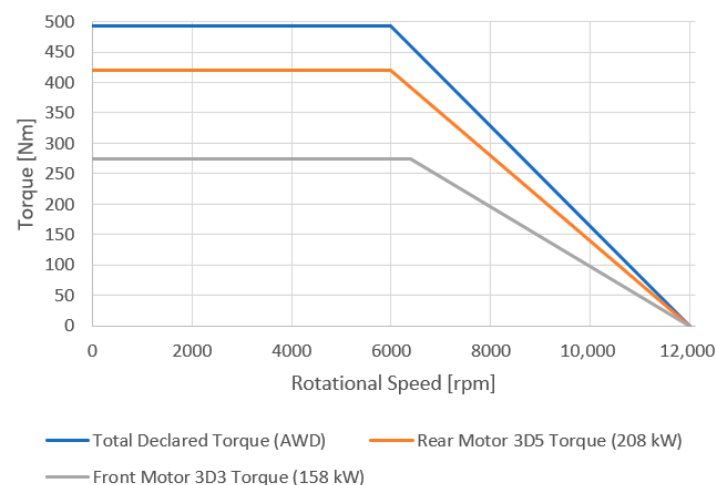


Figure 9. Diagram of the electric motors of the Tesla Model 3 (2020) dual motor.

The development of the dynamic model requires identifying all resistive forces acting on the vehicle during motion, complemented by the inclusion of the driver model, the WLTP speed profile, the transmission system, and the parameterized electric motor model. A lithium-ion battery was incorporated into the model as an equivalent circuit with an RC parallel circuit added to the basic Rint model (Thevenin model), which was parameterized with battery data. The state-of-charge estimation of the battery used in the Simulink model was established by considering the model presented in [60].

The velocity profile was modelled in Simulink using the 'Repeating Table' block, with Excel datasets corresponding to the four slope values imported for each measurement. Figure 10 presents the shortened Type 1 cycle profile applied to simulations on a horizontal road.

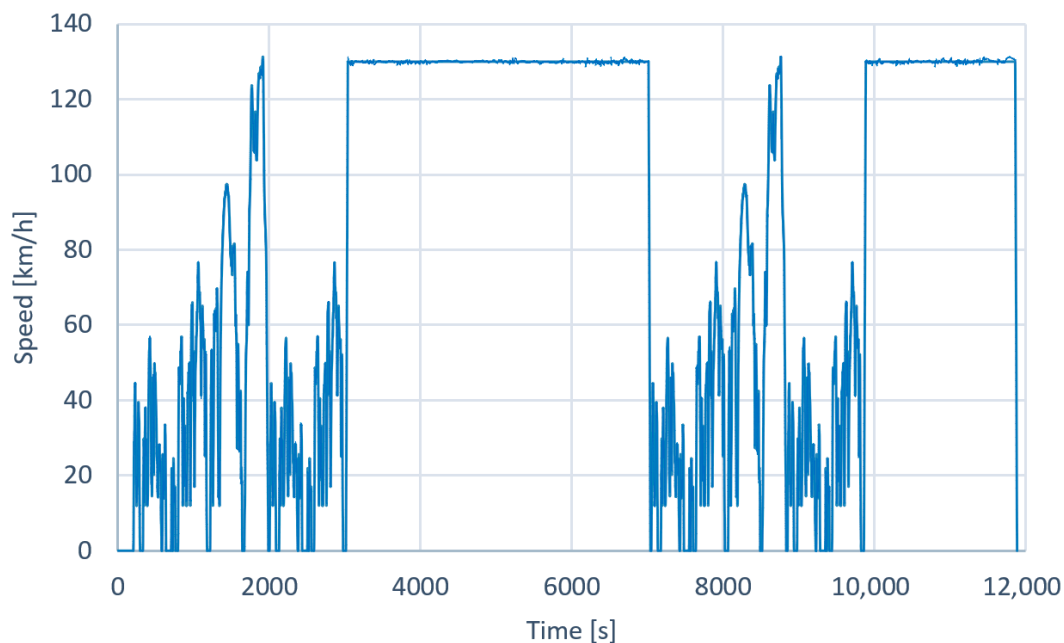


Figure 10. The velocity profile used in Simulink for the horizontal case.

In electric vehicles (EVs), the transmission architecture is typically simplified to either a single-speed reduction gearbox or a direct drive configuration, which transmits mechanical power from the traction motor to the drive wheels. This design choice is enabled by the intrinsic characteristics of electric machines, which exhibit a substantially broader operational speed range than internal combustion engines and are capable of delivering peak torque from standstill (zero revolutions per minute). Consequently, the conventional requirement for a multispeed gearbox is eliminated, thereby reducing drivetrain complexity while maintaining effective performance [61].

In electric vehicles (EVs), the propulsion system relies on an electric motor to deliver the torque and power necessary for vehicle motion. Several motor technologies are suitable for this application, including brushless direct current (BLDC) motors, permanent magnet synchronous motors (PMSMs), and induction motors. The selection of motor type is determined by design requirements and performance objectives, enabling flexibility in optimizing efficiency, cost and drivability characteristics.

The proposed modelling framework establishes a foundational basis for subsequent research aimed at investigating diverse strategies for energy optimization. Owing to its generalizable structure, the model can be applied across multiple optimization methodologies, thereby supporting comparative analyses and the development of advanced techniques for improving electric vehicle efficiency.

To ensure fidelity, the parameters utilized in the simulated and modelled vehicle were aligned with those of the physical counterpart. The resulting measurements of the real vehicle subjected to dynamometer testing were employed to validate the accuracy of the simulation outcomes.

3. Results and Discussion

3.1. Dynamometer Test Results

The driving range of the Tesla vehicle was experimentally evaluated on a dynamometer. In order to replicate real-world driving conditions, the dynamometer software incorporates road load simulation, including the effect of longitudinal slope. Slope resistance is mathematically modelled as an additional tractive force. By programming the dynamometer's eddy current brake torque to match the calculated slope resistance, the system reproduces the increased energy demand associated with uphill driving. They permit manual input of gradient values so that the dynamometer can replicate uphill driving conditions during standardized test cycles. This methodology ensures that the simulated vehicle performance and energy consumption are consistent with real-world conditions, thereby enabling accurate validation of range and efficiency measurements.

The *AASHTO Geometric Design of Highways and Streets* ("Green Book") includes several tables specifying maximum and recommended longitudinal grades for different roadway classifications and design speeds. These tables define allowable slope ranges depending on the terrain type (level, rolling, and mountainous) and road category (freeways, arterials, collectors, and local roads), as presented in Table 2.

Table 2. Maximum grades by design speed and terrain (adapted from AASHTO Green Book, Chapter on Vertical Alignment).

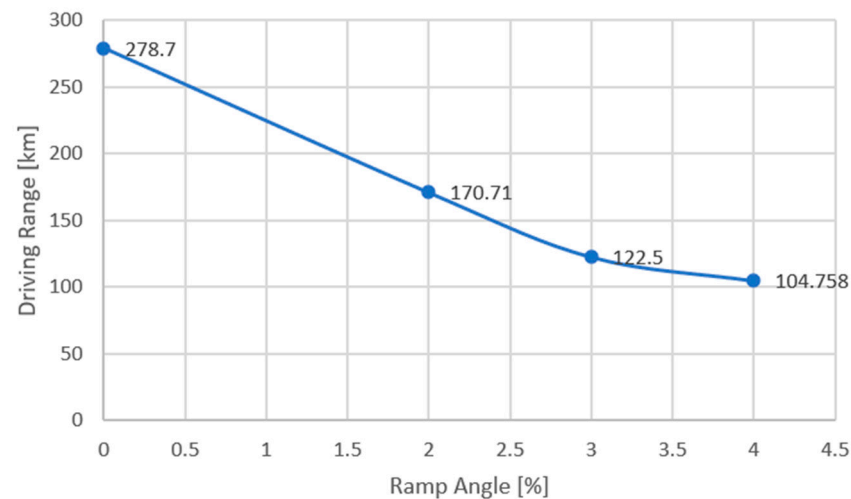
Design Speed [km/h]	Level Terrain [%]	Rolling Terrain [%]	Mountainous Terrain [%]
120	3	4	5
100	4	5	6
80	5	6	7

The measurements were carried out for four ramp angle values—0%, 2%, 3% and 4%—using shortened Type 1 driving cycles. The experimental design focuses on mild longitudinal grades, as these are prevalent in urban traffic and strongly influence vehicle energy use, speed choice and comfort. In road engineering practice, longitudinal grades of a few percent are typically adopted on urban streets to satisfy drainage and safety requirements without imposing excessive demands on vehicle performance. Accordingly, we selected grade values of 2%, 3% and 4%, which span a realistic range from gentle to moderate slopes in built-up environments. We do not aim to reproduce the exact grade distribution of any specific city; instead, our goal is to study vehicle behaviour under representative urban slope conditions that cover the most frequently encountered mild gradients. The choice of a maximum road slope of 4% reflects a methodological decision rather than a limitation of the test bench itself, as the experimental setup is fully capable of accommodating higher gradient values if required.

The recorded driving distance corresponds directly to the number of cycles required to discharge the battery from 80% to 10% state of charge. Within these standardized cycles, vehicle speeds reached up to 131.3 km/h, thereby ensuring that gradient effects were represented in the test results. The measured ranges are summarized in Table 3, and Figure 11 provides their graphical representation.

Table 3. Measured driving range at different ramp angles (SOC: 80–10%).

Ramp Angle [%]	Ramp Angle [°]	Driving Range [km]
0	0	278.70
2	1.145	170.71
3	1.718	122.50
4	2.290	104.76

**Figure 11.** Driving range of Tesla EV as a function of ramp angle, measured on a dynamometer with SOC varying between 80% and 10%.

The ramp angle expressed in degrees was obtained from the relation $\alpha[^\circ] = \arctan(\alpha[\%]/100)$.

The results reveal a strong inverse relationship between ramp angle and achievable driving range. At a flat ramp (0%), the vehicle achieved a maximum range of 278.7 km, while at a 4% gradient, the range decreased to 104.76 km, corresponding to a reduction of more than 62%. This trend is consistent with theoretical expectations, as increasing the ramp angle requires higher torque output from the motor, thereby elevating energy consumption and reducing effective range.

The dynamometer setup provided controlled and repeatable conditions, ensuring that the observed reductions in range are attributable to the gradient effect rather than external variability. This graphical abstract illustrates the inverse relationship between ramp angle and driving range for a Tesla electric vehicle tested on a dynamometer. As the ramp angle increases from 0% to 4%, the driving range decreases sharply, highlighting the impact of road gradient on energy consumption and vehicle efficiency.

As shown in Figure 12a,b, the measurement corresponding to the 2% slope (green) exhibited a deviation in the CSS_M segment at the target speed of 130 km/h. At time 5657 s, the vehicle was no longer able to maintain 130 km/h; its speed dropped to 121.67 km/h within 1.6 s and then recovered to 130 km/h s. Additionally, because energy consumption is lower at this gradient, even a small delay in stopping the test has a proportionally larger impact on the final recorded distance. Moreover, the SOC value displayed on the dashboard is rounded to whole percentages, meaning that the actual 10% threshold may be reached slightly earlier than the moment when the display updates. Under slow discharge conditions, the transition from approximately 11.x% to 10.x% can take longer, introducing an additional small timing variation. While a minor delay in stopping the measurement at the 2% slope cannot be entirely excluded, these factors collectively explain the slightly longer recorded driving distance.

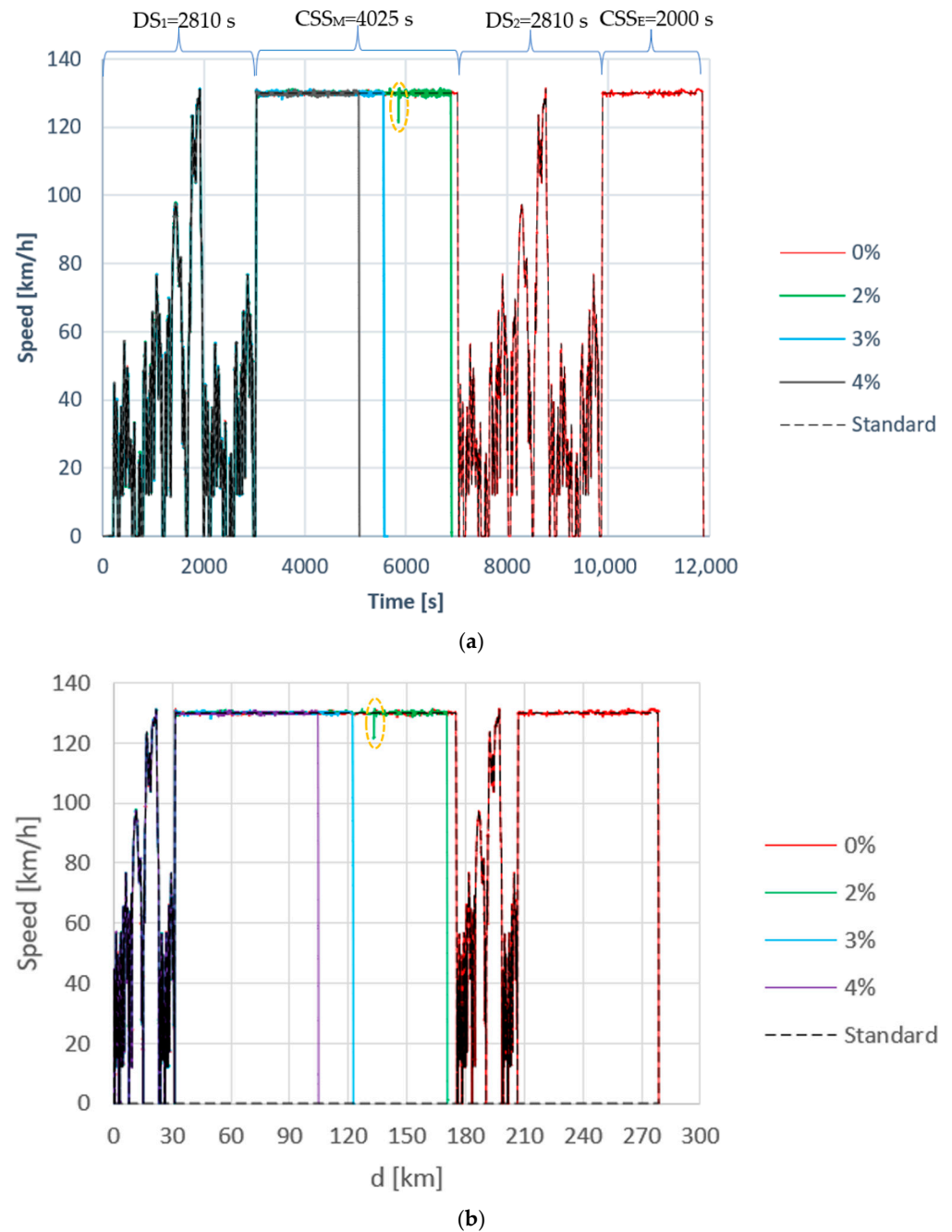


Figure 12. (a) Velocity profiles followed by the driver for each case of angles, measured on the dynamometer with SOC varying between 80% and 10%. (b) Speed profile as a function of the distance driven d for each case of angles, measured on the dynamometer with SOC varying between 80% and 10%. The yellow circle indicates the deviation observed in the CSS_M segment during the 2% slope measurement.

3.2. Simulink Test Results

3.2.1. Model Validation

To validate the Simulink model, appropriate values are adopted for the battery capacity and for the energy consumed by auxiliary systems, ensuring the best possible agreement with the experimental data.

The experimental results consist of the ranges obtained for the four slope values. Therefore, the first step in the validation process is to reproduce these ranges in simulation, matching those measured on the dynamometer. The simulation results, compared with the experimental data, are presented in Table 4.

Table 4. Comparison of driving range obtained in simulation and experiment.

Ramp Angle [%]	Simulink Range [km]	Dynamometer Range [km]	Error [%]
0	265	278.7	−4.916
2	154.4	170.7	−9.549
3	128.6	122.5	4.980
4	109.8	104.76	4.811

Overall, the simulation results show a good level of agreement with the experimental data, with deviations remaining within a reasonable range for this type of study. It is important to emphasize that the experimental tests were performed on a five-year-old vehicle, for which its battery, powertrain components and auxiliary systems may no longer exhibit the performance characteristics of a new vehicle. Natural degradation processes—such as reduced battery capacity, increased internal resistance and mechanical wear—can influence the measured driving range and contribute to discrepancies between simulation and experiment. Additionally, the dynamometer procedure inherently involves human-factor variability, including pedal input, stabilization time and minor fluctuations in operating conditions. These small variations, although unavoidable in practical testing, can introduce measurement uncertainty. Other factors, such as tire condition, may also influence the recorded values.

The deviation observed in the 2% slope test is attributable to some errors during the experimental procedure, as detailed in Section 3.1. Despite these influences, the model successfully captures the overall trend of decreasing driving range as the ramp angle increases. The errors observed at low slopes (0–2%) indicate a slight underestimation of the vehicle’s performance, while at higher slopes (3–4%), the model tends to slightly overestimate the range. This shift suggests that certain slope-dependent losses—such as rolling resistance or drivetrain efficiency—may require further refinement to better reflect real-world behaviour across the entire operating range.

Nevertheless, the magnitude and consistency of the results demonstrate that the Simulink model provides a reliable approximation of the vehicle’s behaviour, even when compared against measurements influenced by aging components and operational variability. These findings confirm that the model is suitable for further analysis and optimization, with targeted improvements expected to enhance its predictive accuracy.

To provide an additional validation reference, two WLTC simulations were performed for initial state-of-charge (SOC) levels of 100% and 80%, as shown in Table 5.

Table 5. Driving range obtained in simulation mode during a WLTC cycle for SOC 100% and 80%.

Cycle	Simulink Range [km]
WLTC SOC 100	513.7
WLTC SOC 80	400.1

The Simulink model estimates a WLTC driving range of 513.7 km at 100% SOC and 400.1 km at 80% SOC. In comparison, the manufacturer’s declared range of 560 km (Figure 5) corresponds to a new vehicle tested at full charge under certification conditions. The simulated value, therefore, reflects an 8% reduction relative to the certified range. This deviation is consistent with the condition of the vehicle used in the present study, which had accumulated 92,250 km. As reported in [62,63], the battery capacity of this vehicle had decreased from its nominal 234 Ah to 221 Ah, representing a degradation of approximately 5.6%. Such a reduction in usable capacity naturally leads to a proportional decrease in achievable driving range. The close correspondence between the simulated

range reduction and the expected impact of battery aging supports the validity of the Simulink model and confirms that it accurately captures the influence of capacity fade on real-world range performance.

The simulated range at 80% SOC (400.1 km) represents approximately 78% of the simulated range at 100% SOC (513.7 km). This proportionality closely reflects the nominal SOC ratio, indicating that the model preserves a realistic scaling of available driving range with respect to the usable battery energy. The slight deviation from the ideal linear relationship can be attributed to the reduced efficiency of the powertrain and auxiliary systems at lower SOC levels, as well as the diminished usable capacity of the aged battery. Overall, the consistency between the SOC-dependent range values further supports the validity of the Simulink model in reproducing the expected behaviour of an aged traction battery under WLTC conditions.

3.2.2. Analysis of Energy Consumption in WLTC Phases

A transition from expressing the results in terms of driving range (km) to energy consumption (Wh/km) is necessary to provide a more robust and comparable assessment of the vehicle's performance. While the driving range is strongly influenced by the initial state of charge, battery aging and test-specific conditions, the energy consumption metric offers a normalized indicator that is independent of the battery's usable capacity. This makes Wh/km a more suitable parameter for evaluating the efficiency of the propulsion system and for comparing different operating scenarios, vehicle conditions or simulation configurations.

Moreover, as the tested vehicle had accumulated significant mileage and exhibited reduced battery capacity, the use of driving range alone could lead to misleading interpretations. By analysing the energy consumption, the influence of battery degradation and SOC variations is effectively decoupled from the vehicle's intrinsic efficiency. This approach ensures a more accurate validation of the model and enables a clearer comparison between simulated and experimental results across different test conditions.

Using the same Simulink model, the energy consumption was calculated for the same slope values, considering both uphill and downhill driving conditions. The results are summarized in Table 6.

Table 6. Uphill and downhill consumptions for the slope values used in the dynamometer analysis.

Ramp Angle [%]	Uphill Consumption [Wh/km]	Downhill Consumption [Wh/km]
0	189.3	-
2	318.6	74.63
3	378.8	12.22
4	439.2	−41.35

The results in Table 6 highlight the expected increase in energy consumption during uphill driving as the ramp angle becomes steeper. This trend reflects the additional mechanical work required to overcome gravitational forces at higher slopes. All EVs' energy consumptions are affected proportionally by the gravitational force, which leads to similar slope-induced consumption trends across vehicle classes. Conversely, the downhill scenarios show a progressive reduction in energy consumption, with values becoming significantly lower—and even negative at a 4% slope—indicating that the vehicle is able to recuperate energy through regenerative braking. Such negative values are consistent with electric vehicle behaviour, where the traction motor operates in generator mode and returns energy to the battery during descent.

These findings confirm that the Simulink model accurately captures the fundamental physical mechanisms governing both traction demand and energy recuperation. The clear distinction between uphill and downhill consumption further supports the validity of the model and provides a more detailed understanding of how slope influences the vehicle's overall energy efficiency.

To gain a deeper understanding of how road slope affects the driving range of electric vehicles, an energy consumption analysis was performed for both uphill and downhill conditions across the four WLTC phases. This approach reflects a common real-world scenario in which a vehicle travels to a destination and then returns along the same route—such as a typical daily commute—allowing the net effect of positive and negative slopes to be evaluated. The results presented in Table 7 provide a comprehensive view of how road slope influences the energy consumption of an electric vehicle across the four WLTC phases.

Table 7. Average energy consumption (Av.) for uphill and downhill conditions at four slope levels, compared with the 0% gradient case over all WLTC phases.

Ramp Angle [%]	Energy Consumption in Phases [Wh/km]				
	Low	Medium	High	Extra High	Complete Cycle
0	116	116.7	128.1	171.9	139.7
1	175.1	177	189.5	233.5	200.6
−1	57.39	57.1	67.8	113.3	79.62
Av.(1) *	116.245	117.05	128.65	173.4	140.11
2	235.1	237.9	251.3	295.4	262
−2	−0.0974	−1.166	8.929	51.62	20.85
Av.(2) *	117.501	118.367	130.114	173.51	141.425
3	295.7	299.4	313.3	357.5	328.8
−3	−56.66	−57.62	−47.5	−6.8	−36.34
Av.(3) *	119.52	120.89	132.9	175.35	146.23
4	356.8	361	375.6	419.8	385.8
−4	−112.3	−112.8	−101.8	−63.3	−91.81
Av.(4) *	122.25	124.1	136.9	178.25	146.995

* Av.(x) = Average energy consumption associated with bidirectional driving on a roadway featuring a ramp angle of x%.

By evaluating both uphill and downhill conditions and then averaging their values, the analysis reflects a realistic round-trip scenario in which a driver travels to a destination and returns along the same route. This approach is particularly relevant for daily commuting patterns, where the net effect of positive and negative gradients determines the actual energy demand experienced by the user.

As expected, uphill segments lead to a substantial increase in energy consumption, with higher slopes producing progressively larger values across all WLTC phases. Conversely, downhill driving results in significantly lower consumption and, in some cases, negative values, indicating effective regenerative braking and energy recuperation.

When the uphill and downhill values are averaged, the resulting consumption remains close to the horizontal (0%) reference case, especially for moderate slopes. This demonstrates that, over a complete out-and-back trip, the net energy impact of road gradients is considerably reduced. A histogram of these results is shown in Figure 13.

The slight increase in average consumption with higher slope magnitudes reflects the fact that regenerative braking cannot fully compensate for the additional energy required during ascent. Nonetheless, the relatively small deviation from the flat-road baseline highlights the robustness of the vehicle's energy management system and the effectiveness of regenerative braking in mitigating slope-related energy losses.

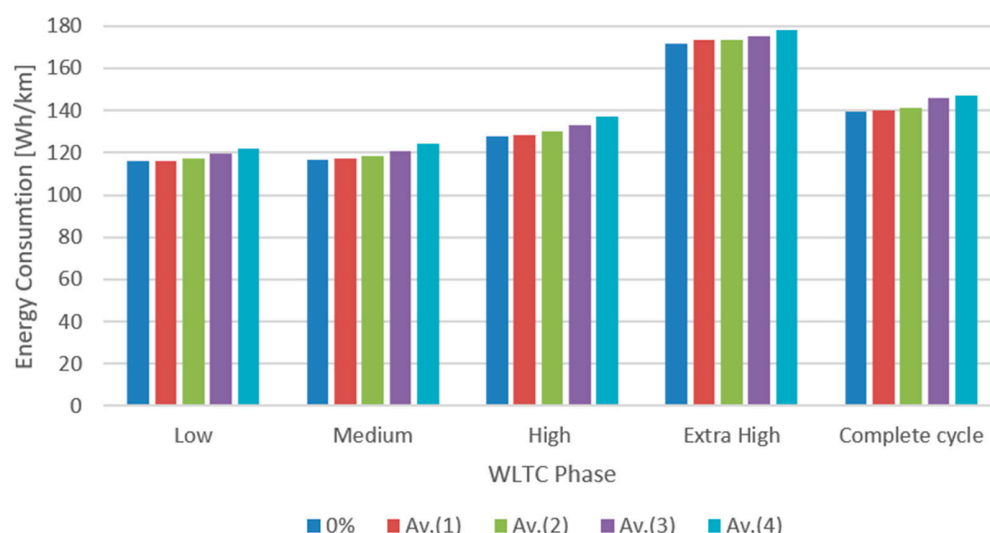


Figure 13. Average energy consumption in uphill and downhill driving for the four slope values versus the flat-road case (0%) over the WLTC phases.

Overall, this analysis confirms that evaluating both uphill and downhill conditions provides a more realistic and balanced assessment of vehicle performance, and it reinforces the validity of the simulation model in capturing the combined effects of slope on energy consumption.

Table 8 summarizes the relative increase in average energy consumption for bidirectional driving on roadways with ramp angles ranging from 1% to 4%, reported for each WLTC phase and for the complete WLTC cycle. Figure 14 presents a graphical representation of these results.

Table 8. Relative increase in average energy consumption for all WLTC Phases and for the complete WLTC Cycle.

Average Case	Relative Energy Consumption Increase [%]				
	Low	Medium	High	Extra High	Complete Cycle
Av.(1)	0.211	0.299	0.429	0.873	0.293
Av.(2)	1.294	1.428	1.572	0.937	1.235
Av.(3)	3.034	3.590	3.747	2.007	4.674
Av.(4)	5.388	6.341	6.870	3.694	5.222

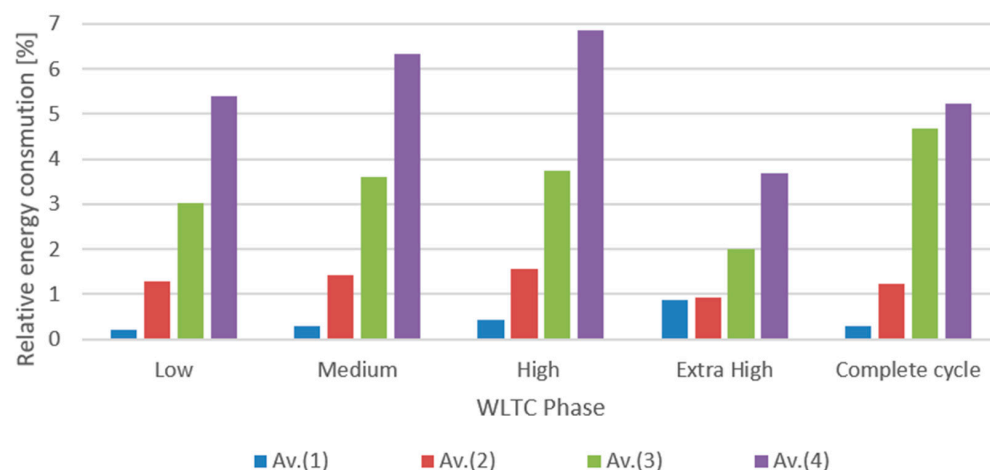


Figure 14. Relative increase in average energy consumption values for all WLTC phases and for the complete WLTC cycle.

The relative energy consumption values in Table 8 show a consistent and expected increase with ramp angle across all WLTC phases. Even though the absolute percentages remain small at low slopes, the progression reveals how sensitive electric vehicle efficiency becomes as the gradient increases.

For mild slopes of 1–2%, the relative increase in average energy consumption associated with bidirectional driving remains below 1.5% in the low and medium WLTC phases. Because these phases involve lower speeds and reduced aerodynamic loading, the additional gravitational demand introduced by the slope is limited. Nevertheless, the upward trend indicates that even slight gradients begin to measurably affect energy usage.

As vehicle speed rises, the influence of the slope becomes more pronounced. For ramp angles of 3–4%, the relative increase in average consumption grows substantially—reaching approximately 3–7% in the high phase and around 2–4% in the extra-high phase.

The extra-high phase exhibits slightly smaller relative increases compared with the high phase, as aerodynamic drag dominates at high speeds, reducing the proportional contribution of the slope.

Overall, these results show that mild gradients (1–2%) impose a modest but detectable increase in energy demand, whereas moderate gradients (3–4%) lead to a marked rise in relative consumption, confirming that sustained slopes significantly affect real-world driving range.

The relationship between slope and energy consumption is nonlinear, with the effect becoming particularly pronounced beyond a 2% gradient. This trend is further intensified in the higher WLTC phases, where the vehicle must counter both gravitational and aerodynamic loads. The full-cycle results also demonstrate that even moderate inclines can noticeably reduce the effective driving range, underscoring the sensitivity of electric-vehicle efficiency to road gradient.

These findings validate the model’s ability to capture slope-dependent behaviour and underline the importance of including gradient effects in range prediction and energy-management strategies.

3.2.3. Analysis of Energy Consumption at Constant Speeds

To complement the WLTC-based investigation and to better isolate the influence of road gradient on electric-vehicle efficiency, an additional analysis was performed at two constant speeds: 130 km/h, representing the legal speed limit on highways, and 50 km/h, corresponding to the typical speed limit in urban areas. Studying these two operating points makes it possible to separate the effects of aerodynamic drag (dominant at high speed) from those of rolling resistance and gravitational load (more relevant at low speed).

For each speed, the vehicle was simulated on the same four positive slopes—1%, 2%, 3%, and 4%—and the corresponding uphill, downhill and average energy consumptions were computed. The average value between uphill and downhill represents a realistic round-trip scenario, where the vehicle travels in both directions on the same road. To quantify the impact of slope, the relative energy consumption was calculated by comparing each averaged value with the horizontal reference case (0% slope). This approach provides a clear and normalized measure of how much additional energy is required due to the road gradient.

Table 9 presents the relative energy consumption at 130 km/h on flat terrain as well as on four different inclined slopes.

At 130 km/h, the uphill energy consumption increases linearly with slope, rising from 204.2 Wh/km on flat ground to 457.6 Wh/km at a 4% incline. This strong increase reflects the combined effect of gravitational load and high aerodynamic drag.

Table 9. Relative energy consumption at 130 km/h on flat terrain and four inclined slopes.

Energy Consumption at Constant Speed ($v = 130$ km/h)					
Ramp angle [%]	0	1	2	3	4
Uphill E * [Wh/km]	204.2	267.6	331	394.3	457.6
Downhill E * [Wh/km]	-	140.7	77.35	13.99	−39.43
Average E * [Wh/km]	-	204.15	204.175	204.145	209.085
Relative energy consumption [%]	-	−0.024	−0.012	−0.027	2.392

* E = Energy consumed.

Downhill values decrease sharply with slope, becoming negative at 4%, which indicates net energy recuperation through regenerative braking.

Despite the large differences between uphill and downhill values, the average consumption remains remarkably stable, around 204 Wh/km for slopes of 1–3% and slightly higher (209 Wh/km) at 4%.

This stability occurs because at high speeds, aerodynamic drag dominates, and the additional gravitational component—although large uphill—is nearly compensated by regenerative braking downhill.

The relative consumption values reinforce this trend, showing changes that remain near zero or even slightly negative for slopes between 1% and 3%, followed by a modest increase of 2.39% at a 4% incline.

This means that at highway speeds, moderate slopes have almost no net effect on round-trip energy consumption, except when the gradient becomes steep enough that regenerative braking cannot fully compensate for the uphill demand.

Table 10 presents the relative energy consumption at 50 km/h on flat terrain and on four different inclined slopes.

Table 10. Relative energy consumption at 50 km/h on flat terrain and four inclined slopes..

Energy Consumption at Constant Speed ($v = 50$ km/h)					
Ramp angle [%]	0	1	2	3	4
Uphill E * [Wh/km]	92.38	155.8	219.2	282.5	345.8
Downhill E * [Wh/km]	-	28.96	−26.18	−77.77	−129.3
Average E * [Wh/km]	-	92.38	96.51	102.365	108.25
Relative energy consumption [%]	-	0	4.471	10.809	17.179

* E = energy consumed.

At 50 km/h, uphill consumption increases significantly with slope, from 92.38 Wh/km at 0% to 345.8 Wh/km at 4%. Downhill values become strongly negative at higher slopes, reaching −129.3 Wh/km at 4%, indicating substantial energy recuperation.

Unlike the 130 km/h case, the average consumption increases steadily with slope. At low speeds, aerodynamic drag is small, so gravitational effects dominate, and regenerative braking cannot fully compensate for the uphill energy demand.

The relative increases are substantial. This shows that at urban speeds, road gradients have a strong and nonlinear impact on energy consumption, significantly affecting real-world range in hilly cities.

So, at highway speeds (130 km/h), the slope has minimal net effect on round-trip energy consumption because aerodynamic drag dominates and downhill recuperation nearly balances uphill demand. At urban speeds (50 km/h), the slope has a major impact, with relative consumption increasing up to 17% at a 4% gradient.

These results highlight the importance of considering the driving environment when estimating EV range: highways are less sensitive to slope, and urban and suburban areas with frequent gradients can significantly reduce efficiency.

The constant-speed simulations at 130 km/h and 50 km/h provide valuable insight into how road gradient affects electric-vehicle energy consumption under simplified, steady-state conditions. The results clearly show that the influence of slope is strongly dependent on vehicle speed. At highway speeds, the dominant aerodynamic drag minimizes the net effect of gradient, leading to almost unchanged average consumption for slopes up to 3% and only a modest increase at 4%. In contrast, at urban speed, where aerodynamic forces are much smaller, the gravitational component becomes the primary driver of energy demand. As a result, average consumption increases progressively with slope, reaching more than 17% at a 4% gradient. These findings highlight the importance of considering the driving environment when estimating real-world range: while highways are relatively insensitive to slope, urban and suburban routes with frequent gradients can significantly affect energy efficiency and daily driving autonomy.

4. Discussion

The experimental evaluation of the Tesla vehicle's driving range on a chassis dynamometer provides a detailed perspective on how longitudinal road gradients influence electric vehicle performance. By incorporating road load simulation, including the effect of slope, the test setup closely replicates real-world driving conditions and aligns with previous studies emphasizing the importance of controlled yet realistic laboratory environments for assessing EV efficiency. The selected ramp angles—0%, 2%, 3%, and 4%—reflect typical gradients encountered in urban road networks, where mild slopes are introduced primarily for drainage and safety considerations. This choice supports the working hypothesis that even small variations in roadway inclination can meaningfully affect vehicle energy consumption.

The methodology, based on repeated shortened Type 1 driving cycles until the battery was discharged from 80% to 10% SOC, ensured that the measured driving distance directly reflected the vehicle's energy demand under standardized conditions.

The results reveal a pronounced inverse relationship between ramp angle and achievable driving range. While the vehicle reached 278.7 km on flat ground, the range decreased to 104.76 km at a 4% gradient—a reduction exceeding 62%. This outcome is fully aligned with theoretical expectations and the prior literature, which consistently report that increasing slope requires higher motor torque and consequently elevates energy consumption. The magnitude of the observed reduction underscores the sensitivity of the EV range to even moderate gradients, reinforcing the need to integrate slope effects into predictive energy consumption models, navigation algorithms and eco-routing strategies.

Model validation using the Simulink framework shows encouraging agreement with the experimental data. By adopting appropriate values for battery capacity and auxiliary-system energy consumption, the model reproduces the overall trend of decreasing range with increasing slope. The deviations observed—slight underestimation at low slopes and slight overestimation at higher slopes—are within acceptable limits for this type of study and can be interpreted in the context of the tested vehicle's condition. The five-year-old vehicle had accumulated over 92,000 km, and its battery and drivetrain components likely exhibit performance degradation not present in a new vehicle.

The simulated driving range at 100% SOC shows an 8% reduction relative to the manufacturer's certified value, a deviation consistent with the vehicle's measured battery degradation. Transitioning from driving range (km) to energy consumption (Wh/km) provides a more robust and comparable assessment of vehicle performance, as energy consumption is independent of initial SOC and usable battery capacity.

Using the same Simulink framework, energy consumption was evaluated for the four slope values under both uphill and downhill driving conditions. Uphill driving

produced progressively higher energy consumption as the ramp angle increased, reflecting the additional mechanical work required to overcome gravitational forces. Conversely, downhill driving yielded substantially lower consumption, with values becoming negative at a 4% slope due to regenerative braking. These negative values are consistent with established EV behaviour, where the traction motor operates in generator mode and returns energy to the battery during descent.

To provide a more realistic representation of everyday driving, the analysis was extended across the four WLTC phases for both uphill and downhill conditions. This bidirectional approach mirrors common real-world scenarios—such as commuting routes where drivers travel to a destination and return along the same path—allowing the net effect of positive and negative slopes to be assessed. Across all WLTC phases, uphill segments consistently increased energy consumption, while downhill segments reduced it, often substantially. When averaged, the resulting energy consumption remained close to the horizontal (0%) reference case, particularly for moderate slopes. This finding indicates that, over a complete out-and-back trip, the net energy impact of typical road gradients is significantly reduced not only by regenerative braking but also by the lower traction demand during downhill segments, which jointly mitigate the overall gradient-related energy effect.

The slight increase in average consumption at higher slope magnitudes reflects the fact that regenerative braking cannot fully compensate for the additional energy required during ascent. Nonetheless, the relatively small deviation from the flat-road baseline demonstrates the robustness of the vehicle's energy-management system and highlights the effectiveness of regenerative braking in mitigating slope-related energy losses. These results confirm that evaluating both uphill and downhill conditions provides a more realistic and balanced representation of electric-vehicle performance and reinforces the validity of the simulation model in capturing the combined effects of slope on energy consumption.

The relative energy consumption values exhibit a consistent and expected increase with ramp angle across all WLTC phases. Although the absolute percentages remain small at mild slopes, the progressive rise underscores the sensitivity of electric vehicle efficiency to even modest changes in gradient. For slopes of 1–2%, the relative increase in average energy consumption remains below 1.5% in the low and medium phases, where lower speeds and reduced aerodynamic loading limit the gravitational impact. As vehicle speed increases, the effect of the slope becomes more pronounced. For ramp angles of 3–4%, the relative increase grows substantially—reaching approximately 3–7% in the high phase and around 2–4% in the extra-high phase. These findings are consistent with established theoretical models and prior empirical studies, which similarly report that slope effects scale with speed and drivetrain load.

To further isolate the influence of road gradients on electric vehicle efficiency, an additional analysis was conducted at two constant speeds: 130 km/h, representative of highway driving, and 50 km/h, typical of urban environments. At 130 km/h, uphill consumption increased sharply with slope, but the average round-trip consumption remained nearly constant because aerodynamic drag dominated and downhill recuperation nearly balanced uphill demand. In contrast, at 50 km/h, where aerodynamic forces are much smaller, gravitational effects dominated, and regenerative braking could not fully offset the uphill energy requirement. As a result, average consumption increased progressively with slope, reaching more than 17% at a 4% gradient. These findings highlight the importance of considering the driving environment when estimating real-world ranges: while highways are relatively insensitive to slope, urban and suburban routes with frequent gradients can significantly affect energy efficiency and daily driving autonomy.

Overall, the results confirm the working hypothesis that road gradients exert a substantial influence on EV energy consumption and range. They also emphasize the broader implication that accurate range prediction requires models capable of capturing both environmental factors and vehicle-specific aging effects. Future research could extend this work by incorporating temperature effects, battery-degradation models and real-world driving data, as well as by exploring adaptive control strategies that optimize energy use on varying terrain. Such developments would further enhance the predictive accuracy of simulation tools and support more reliable range estimation in practical applications.

5. Conclusions

This study investigated the influence of longitudinal road gradient on the energy consumption and driving range of a Tesla electric vehicle through a combination of dynamometer measurements and detailed Simulink simulations. The experimental results demonstrated a strong inverse relationship between slope and achievable range, with gradients as low as 3–4% producing substantial reductions in driving autonomy. These findings confirm that even moderate inclines impose significant additional energy demand, underscoring the importance of incorporating gradient effects into real-world range estimation and energy-management strategies.

The Simulink model showed good agreement with the experimental data, successfully reproducing the observed trends despite the aging condition of the tested vehicle. The slight deviations at low and high slopes suggest that further refinement of slope-dependent losses could enhance predictive accuracy. Transitioning from driving range to energy consumption metrics provided a more robust basis for comparison, effectively decoupling the influence of battery degradation and SOC variations from the vehicle's intrinsic efficiency.

The analysis of uphill and downhill conditions across WLTC phases revealed that regenerative braking plays a crucial role in mitigating slope-related energy losses, particularly over round-trip scenarios. While uphill segments substantially increase consumption, downhill recuperation offsets much of this demand, resulting in average values that remain close to the flat-road baseline for moderate slopes. Constant-speed simulations further highlighted the strong dependence of slope effects on vehicle speed: at highway speeds, aerodynamic drag dominates and minimizes net gradient impact, whereas at urban speeds, gravitational forces become the primary driver of energy demand.

Overall, the results confirm the working hypothesis that road gradients are a key determinant of electric vehicle efficiency and must be explicitly considered in predictive models, eco-routing algorithms and infrastructure planning. Future research should extend this work by integrating temperature effects, detailed battery-degradation models and real-world driving data and by exploring adaptive control strategies that optimize energy use on varying terrain, including the potential benefits of explicitly optimized regenerative-braking phases. Such developments will support more accurate range prediction and contribute to the broader goal of improving electric vehicle performance in diverse operating environments.

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