

Article

Analysis of Energy Consumption of an Electric Vehicle Prototype with MATLAB/Simulink for Battery Sizing

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Abstract

An integrated model is presented to estimate the energy consumption of a Formula SAE-type electric vehicle by combining MATLAB/Simulink simulations with real operational data from the Cotopaxi kart circuit. The implemented subsystem incorporates vehicle dynamics, speed, and grade profiles, and it enables the calculation of tractive energy across different competition scenarios. The L3 cycle (maximum speed 90.91 km/h, distance 16.67 km) proved the most demanding, with a tractive energy consumption of 1389.10 Wh, mechanical losses of 630.89 Wh, and a useful net energy of 758.21 Wh. Rolling resistance and inertia accounted for 21.33% and 56.29% of the consumption, respectively, highlighting the influence of acceleration/deceleration dynamics. All cycles were dominated by active phases, with 0% stops and cruising time < 0.21%, validating the model for high-demand conditions. The technical feasibility of second-life Lithium Iron Phosphate (LFP) cells for the battery pack was also confirmed: a 30s2p configuration using 100 Ah cells meets the peak energy demand of 18.30 kWh while maintaining adequate operational margin and a safe discharge C-rate. Structural simulation in ANSYS enabled optimization of mass and stiffness, reducing overall energy demand. This multidisciplinary approach provides a quantitative basis for battery sizing and energy management strategies in competitive electric vehicle applications.

Keywords: energy consumption; battery sizing; electric vehicle prototype; MATLAB/Simulink; battery system design



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1. Introduction

There is currently a growing interest in electric propulsion, driven by the urgent need to decarbonize society and prevent a catastrophic climate collapse. Globally, the transportation sector accounts for 18% of total carbon dioxide emissions [1]. To address the imminent risk of climate change, both consumers and industry must adopt sustainable transportation practices aligned with the United Nations Sustainable Development Goals [2]. With the aim of raising awareness of this challenge, Formula SAE, an international university-level competition, has established a dedicated category for electric propulsion systems [3]. The purpose of promoting electric mobility is to achieve greater energy efficiency and reduce greenhouse gas emissions [4]. Through electromobility, new opportunities arise to attain significant environmental benefits, since electric vehicles do not emit tailpipe gases, enabling a more effective approach to the issues of pollution generated by vehicle

emissions [5]. Consequently, electric vehicles have the potential to significantly reduce greenhouse gas emissions from the transportation sector, with battery electric vehicles being the only ones that produce zero local emissions [6]. The transition toward vehicle electrification is crucial to meeting governmental objectives for achieving carbon neutrality. However, this shift faces several technical challenges that demand attention [7]. This policy also impacts the motorsport industry, particularly because electric vehicles have been integrated into competitions such as Formula SAE and Formula E, where they are now considered main categories [8].

Although various fully electric vehicle models are currently available in the market, on-board energy storage systems (ESSs), such as batteries, supercapacitors, or fuel cells, still present performance limitations [9]. Research in this field is experiencing increasing interest and demand, especially in the modeling, design, and control of electric vehicles, as well as in the corresponding energy management. These have become relevant and emerging research topics in this discipline [10]. Accurate modeling, simulation, and validation of the electric drivetrain in electric vehicles (EVs) is essential for making critical decisions in the design and control of high-performance vehicles [11]. From an engineering perspective, propulsion systems and energy storage technologies remain a key area that requires ongoing research and optimization [12].

The accurate estimation of energy consumption in electric vehicles constitutes a fundamental challenge in both vehicle design and energy management. The literature identifies three principal modeling paradigms, each offering different trade-offs between physical fidelity, computational cost, and applicability to specific scenarios.

Quasi-static models:(also termed backward or effect-cause models) assume that the vehicle operates under near steady-state conditions, computing energy demand from a predefined speed profile without resolving transient powertrain dynamics [13]. The Comprehensive Power-Based EV Energy Consumption Model (CPEM) represents a well-established quasi-steady backward model, requiring only instantaneous speed and vehicle characteristics as inputs. These models are computationally efficient and widely adopted for route-level energy planning and battery sizing in passenger electric vehicles; however, their steady-state assumption limits their accuracy under highly transient driving patterns such as those encountered in motorsport applications [14].

Dynamic models: (forward or cause-effect models) resolve the time-dependent interaction between powertrain components, incorporating driver behavior, motor efficiency maps, inverter losses, and regenerative braking control strategies. The forward approach is based on equations of the powertrain components behavior and the dynamic interaction between the components, enabling accurate simulation of transient phenomena. Studies such as those by Miri et al. [15] and Sziki et al. [16] have implemented forward dynamic models in MATLAB/Simulink to reproduce real driving cycles with errors between 2% and 6% relative to experimental measurements. For Formula SAE electric prototypes, where acceleration-dominated driving cycles impose rapid power transients, dynamic models based on longitudinal vehicle dynamics—integrating aerodynamic drag, rolling resistance, grade, and inertial forces—have been shown to provide the necessary resolution to support battery pack sizing [17].

Data-driven approach: leverage machine learning algorithms—including neural networks, gradient boosting, and long short-term memory (LSTM) networks—to predict energy consumption from real-world operational data [18]. Neural network-based models applied to real driving cycles have achieved validation indicators of R^2 up to 86% for summer conditions, demonstrating high predictive accuracy where large datasets are available. However, data-driven models require extensive trip data for training and offer

limited physical interpretability, which constrains their application in first-generation prototype development contexts where empirical data are scarce [19].

In this context, the present study adopts a longitudinal dynamics-based approach consistent with the dynamic modeling paradigm implemented in MATLAB/Simulink. This choice is justified by the highly transient nature of the Cotopaxi Kartodrome driving cycles (characterized by 0% idle time and cruising below 0.21%), the absence of pre-existing trip data for the prototype, and the requirement to generate physically interpretable results suitable for battery pack sizing and structural optimization under realistic competition conditions.

The increasing number of batteries retired from electric vehicles has driven the need to identify second-life battery (SLB) applications to avoid premature disposal. Through a comprehensive literature review and expert interviews, the study by Micheline et al. identified 65 potential applications, classified as mobile, semi-stationary, and stationary. After a technical, economic, and legal assessment, automated guided vehicles (AGVs) and industrial energy storage systems (ESSs) emerged as the most promising options, aligned with expanding markets. The findings confirm the broad potential of SLBs across various sectors, highlighting their viability for low-demand applications and their key role in the circular economy [20].

In the article by Aziziaghdashleh et al., the authors analyze the main challenges, such as usage history uncertainty, safety, and the lack of standardized methods for residual performance characterization. Through an extensive review of measurement techniques (precision vs. complexity) and techno-economic analyses, the study highlights the necessity of rigorous screening protocols and adaptive Battery Management System (BMS) to ensure viability. The results emphasize that although SLBs are promising for stationary energy storage, successful implementation requires advances in degradation monitoring, process standardization, and cost optimization, outlining key research imperatives to extend their service life and maximize their impact on the circular economy [21].

In the study by Akram et al., the authors address the technical challenge of reusing EV batteries with residual capacity (75–80%) in low-energy-demand applications. They propose equivalent circuit models (2RC/3RC) and electrochemical impedance spectroscopy (EIS) to assess degradation. The research emphasizes that electrochemical models and real-world scenario-based tests, supported by AI, enhance aging prediction beyond empirical approaches. Although the recent literature often prioritizes environmental aspects, this study stresses the need to address technical challenges, such as accurate BMS systems and repackaging strategies, to enable the efficient reuse of second-life batteries [22].

Faced with the need for sustainable solutions in academic competitions, this research investigates the feasibility of implementing a Formula Electric prototype powered by second-life batteries. The project aims to combine the structural design of the chassis and bodywork with a dynamic vehicle model to estimate energy consumption under realistic driving conditions. By simulating circuits adapted to karting tracks, the study compares the performance of reused batteries with conventional solutions. This work will provide key data on the capacity, degradation, and thermal stability of lithium-ion batteries, with the goal of promoting circular engineering practices in the field of high-performance electric mobility.

1.1. Objectives

The main objective of this research is to evaluate the energy consumption and technical feasibility of a Formula-type electric prototype powered by second-life batteries. This will be achieved through optimized structural design and dynamic simulation under

realistic competition conditions, aiming to promote sustainable solutions in the field of high-performance electric mobility.

- Design and simulate the Formula Electric prototype by integrating an optimized chassis and bodywork using ANSYS, ensuring rigidity, safety, and weight reduction, while guaranteeing an efficient structural framework that minimizes energy losses due to deformation or inertia.
- Mathematically model the vehicle dynamics and energy consumption using MATLAB/Simulink, incorporating realistic parameters from the Cotopaxi Kartodrome circuit (altitude, elevation profile, speed, and gradient) to quantify energy demand under acceleration, braking, and aerodynamic resistance scenarios.
- Size the prototype's electric battery pack based on the energy analysis of simulated routes, using second-life LFP cells. Establish the optimal series-parallel configuration that ensures compliance with endurance test requirements in terms of autonomy and power delivery.

1.2. Significance and Methodological Contributions

This study addresses a specific and underexplored intersection in the EV engineering literature: the integration of longitudinal vehicle dynamics simulation, real track-based driving cycle data, structural FEA optimization, and second-life battery electrochemical modeling into a unified design framework for a Formula SAE electric competition prototype operating at high altitude (2800 m a.s.l.). Table 1 identifies the four principal methodological contributions of this work and explicitly differentiates each from the closest related studies in the literature.

Table 1. Methodological contributions of the present study and differentiation from related work.

Contribution	This Study	Closest Prior Work	Key Differentiation
C1: Real-track GPS-derived driving cycles at high altitude	Three cycles (L1/L2/L3) from GPS at Cotopaxi Kartodrome (2800 m a.s.l.); altitude-corrected ρ , slope and speed ($V_{max} = 90.91$ km/h; $\theta_{max} = 13.8\%$)	Salek et al.: FSAE track energy. Puma-Benavides et al. high-altitude road driving (Ecuador)	Only study combining FSAE track data with high-altitude GPS instrumentation ($\rho = 0.909$ kg/m ³)
C2: Quantitative structural–energy coupling via ANSYS–Simulink	Chassis FEA (ANSYS) propagated into Simulink; design rule: 105.7 Wh/kg reduction in C_{pack} per kg chassis mass reduction (Equation (11))	Aslan et al.: CATIA + ANSYS + MATLAB; qualitative finding only (>50% energy from design parameters)	Derives specific quantitative mass-to-energy coupling metric usable as structural design objective
C3: Second-life LFP battery sizing with ECM and altitude correction	30s $\times$ 2p sizing: energy balance + Thevenin ECM + thermal model + altitude resistance correction (+7%) + 5-criterion SLB selection framework	Khedkar et al.: energy balance only. Hossain et al.: SLB review, no FSAE application	First SLB sizing for Formula SAE with ECM, thermal, and high-altitude corrections simultaneously
C4: Three-level validation with uncertainty and sensitivity quantification	(1) Energy balance (<0.1%); (2) FSAE benchmark (<8%); (3) Gaussian $u_c = \pm 2.25\%$ + normalized SI ranking	Miri et al.: EPA validation (2–6%). Sziki et al.: MATLAB race car EV validation	Combines indirect benchmark, Gaussian uncertainty, and SI ranking for a competition EV at design stage

These four contributions collectively establish a replicable multidisciplinary framework that advances the current state of the art in three specific directions not simultaneously addressed by any single prior study: (1) GPS-informed competition driving cycle generation at high altitude; (2) quantitative structural-to-energy design coupling; and (3) second-life battery sizing with electrochemical, thermal, and altitude corrections for Formula SAE competition conditions.

2. Materials and Methods

In the context of sustainable electric mobility, energy consumption analysis in competition prototypes becomes critically relevant, particularly when integrating second-life batteries to support the circular economy [23]. This study proposes a multidisciplinary methodology that combines advanced structural design of the chassis and bodywork. The design is optimized through finite element simulations in ANSYS to ensure rigidity, safety, and weight reduction. The analysis is complemented by a vehicle dynamics model developed in MATLAB/Simulink. This model enables simulation of vehicle behavior under realistic conditions, quantifying energy consumption based on variables such as speed profile, slope, power demand, and the resistive forces that must be overcome by the propulsion system.

As a validation scenario, the professional karting track at Cotopaxi (Ecuador) is used, characterized by its high altitude (2800 m above sea level) and technical features that challenge battery autonomy and thermal stability. Through track-based testing and energy consumption analysis, the performance of reused batteries is evaluated, considering residual degradation and power delivery capability.

This research not only aims to optimize the design of the prototype but to also demonstrate the technical feasibility of using second-life lithium batteries in demanding environments. The study contributes key data for their implementation in student competitions, promoting engineering practices aligned with environmental sustainability.

The methodology illustrated in Figure 1 is structured into four interconnected stages: definition, test route, vehicle model development, and analysis and results. In the initial definition stage, the baseline vehicle under study is established, and the test route is described in detail—including geographical and operational parameters. The methodological tools and project scope limitations are also specified.

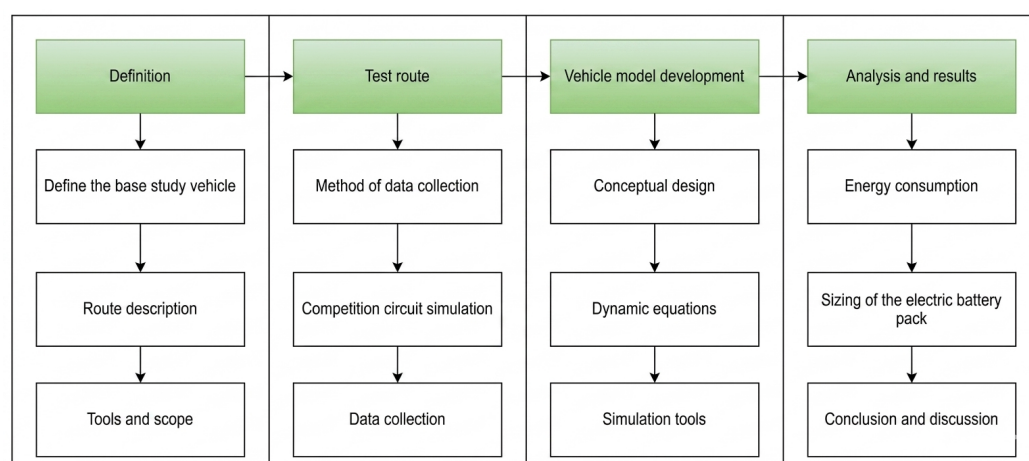


Figure 1. Methodology used to analyze the energy consumption of the simulated electric vehicle.

In the test route stage, a data acquisition protocol is implemented, combining circuit simulation (to replicate real driving conditions) with practical measurements of key variables such as energy consumption and dynamic performance. The third stage—vehicle

model development—integrates the conceptual design of the prototype vehicle, the formulation of dynamic equations that govern its mechanical behavior, and the use of specialized software to simulate various operating scenarios.

Finally, in the analysis and results stage, energy consumption is quantified, and the simulated data are compared against real-world measurements obtained on the test circuit. The resulting conclusions are discussed with a focus on comparative efficiency between technologies and the viability of their application in specific contexts. This systematic approach enables evaluation of both the environmental impact of traditional vehicles and the adaptability of electric alternatives in controlled and realistic scenarios.

2.1. Materials

2.1.1. Vehicle Selection

The model selection and specifications are based on a Formula SAE prototype vehicle, aiming to prioritize a balance between dynamic performance, energy efficiency, and regulatory compliance. The technical characteristics of the Formula prototype are detailed in Table 2. A competitive design integrates a lightweight chassis (tubular or monocoque) that optimizes torsional stiffness and mass distribution, a transmission system with gear ratios adapted to technical circuits, and a minimalist aerodynamic package that reduces drag without compromising downforce in tight corners. For electric vehicles, the battery pack selection must ensure high energy density (Wh/kg) and discharge capability (C-rate), coupled with a high-efficiency electric motor (>90%) using vector torque control. The suspension must allow fine adjustments of camber, toe, and damping to adapt to varying surface conditions, while the tires (slicks or rain) must provide optimal grip in dry or wet conditions. Embedded electronics are critical for real-time monitoring of key parameters and fault prevention.

Table 2. Main characteristics of the Formula SAE Student prototype vehicle.

Characteristic	Typical Specification
Maximum torque (motor)	80 Nm
Maximum power (motor)	20 kW
Total vehicle weight	340 kg (incl. driver and batteries)
Tire size	175/70 R13
Dimensions (L × W × H)	2800 × 1400 × 1100 mm (approx.)
Transmission efficiency	92–96% (chain/belt + differential)

2.1.2. Electric Drivetrain Architecture

Figure 2 presents the simplified block diagram of the electric drivetrain architecture proposed for the Formula SAE electric prototype. The system integrates five principal components interconnected by power and control signal flows. The energy chain originates at the battery pack, consisting of second-life prismatic LiFePO₄ (LFP) cells arranged in a 30s × 2p configuration, supplying high-voltage DC power at a nominal pack voltage of 96 V. The DC power is conditioned by the motor controller (inverter), which performs DC-to-AC conversion and implements torque and speed control through pulse-width modulation (PWM) signals. The conditioned AC power drives the electric motor—a Golden Motor HPM-10KW brushless DC machine operating with high efficiency (>91%), converting electrical energy into mechanical torque. The mechanical power is transmitted through a single-reduction transmission (final drive ratio $\varepsilon_d = 4.33$), which amplifies the motor torque while reducing rotational speed, delivering the tractive force to the wheels (175/70 R13 tires, dynamic radius $r_d = 0.2789$ m) for vehicle propulsion.

Supervisory control is performed by the Vehicle Control Unit (VCU), which coordinates torque demand, regenerative braking activation, and fault detection across all drivetrain subsystems through dedicated control signal channels (dashed lines in Figure 2).

The main energy flow—from DC electrical power through power conversion, mechanical power production, torque multiplication, to traction force—is summarized in the lower section of Figure 2, highlighting the sequential energy transformation stages that govern the overall drivetrain efficiency and the energy consumption model.

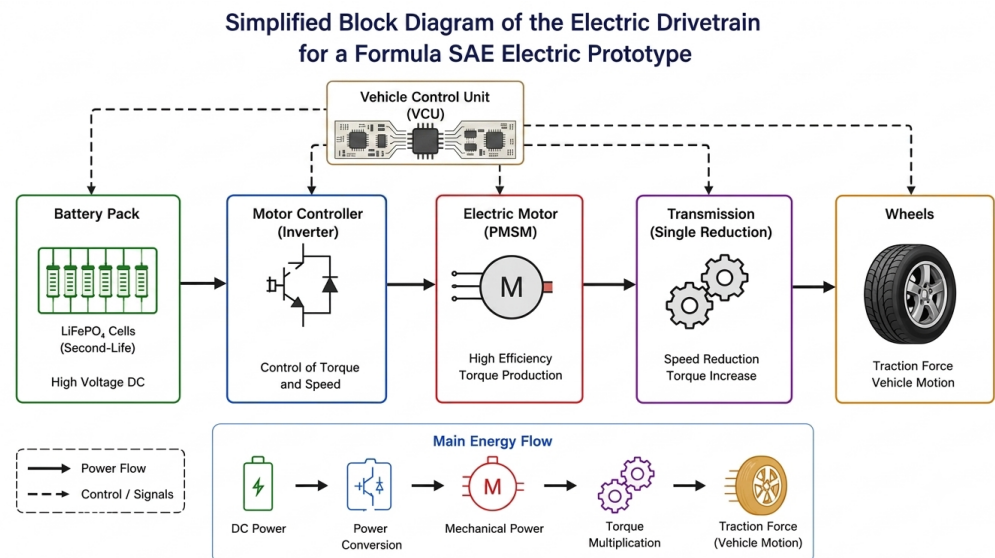


Figure 2. Simplified block diagram of the electric drivetrain for the Formula SAE electric prototype. Solid arrows indicate power flow; dashed arrows indicate control and signal pathways. The lower panel summarizes the sequential energy transformation chain from DC power to traction force.

It is noted that the physical implementation of the drivetrain components—including inverter selection, motor controller programming, and BMS integration—falls outside the scope of the present design and sizing study, and will be addressed in the follow-up publication on prototype construction. The drivetrain architecture shown in Figure 2 serves as the reference system for defining the energy flow boundaries and efficiency parameters (η_t , η_{pack} , η_{motor}) used in the longitudinal dynamics model of Section 2.3.2.

2.1.3. Motor and Power Converter Specifications

The electric propulsion system selected for the Formula SAE prototype consists of the Golden Motor HPM-10KW brushless DC motor paired with the Golden Motor HPC500H Series motor controller (inverter), operating at a nominal pack voltage of 96 V. Table 3 presents the complete electrical and mechanical specifications of both components, as reported in the manufacturer’s official datasheet and controller user guide [24].

2.1.4. Structural Simulation Software

This section details the simulation workflow used to characterize the performance parameters of the Formula competition prototype. The main objective is to integrally evaluate the mechanical and aerodynamic behavior of the chassis, so that, based on the results, a precise estimation of energy consumption can be obtained under different speed and load conditions. To achieve this, the models for dynamic loads and the drag and lift forces associated with the bodywork were configured, ensuring that boundary conditions are adapted to the actual track scenarios.

In the CAD model, the chassis dimensions and topology were explicitly defined, including the length and cross-section of the tubes, joint nodes, and spatial layout of the structural elements. This geometry, developed in accordance with Formula SAE regulations and shown in Figure 3, serves as the basis for subsequent torsional stiffness, vibration, and aerodynamic simulations.

Table 3. Key specifications of the Golden Motor HPM-10KW and HPC500H96400 controller relevant to the energy consumption model and battery sizing analysis (96 V operating configuration).

Component	Parameter	Value	Relevance to Energy Model
Motor	Model	Golden Motor HPM-10KW (BLDC)	—
	Peak power (P_{peak})	20 kW	$I_{peak} = P_{peak} / V_{pack}$ (Equation (43))
	Rated power (continuous)	8–10 kW	Sustained endurance demand
	Peak efficiency	>91%	Contributes to η_{drive}
Motor Controller	Model	Golden Motor HPC500H96400	—
	Peak output current @ 96 V	400 A	Margin vs. $I_{peak} = 208.33$ A (48% margin)
	Maximum efficiency	>98%	$\eta_{drive} > 91\% \times 98\% = 89.2\%$
	Regenerative braking	Yes (programmable)	Hardware basis for $\eta_{regen} = 25\%$ (Equation (35))
System @ 96 V	Combined drivetrain efficiency	>89.2% ($\eta_{motor} \times \eta_{ctrl}$)	Upper bound of η_t in Simulink model
	Controller current margin	+191.67 A above I_{peak}	Confirms motor–controller compatibility

Complete electromechanical specifications (phase resistance, inductance, dimensions, CAN integration) are reserved for the follow-up publication on drivetrain physical implementation. Source: Golden Motor Technology Co., Ltd., Changzhou, China [24].

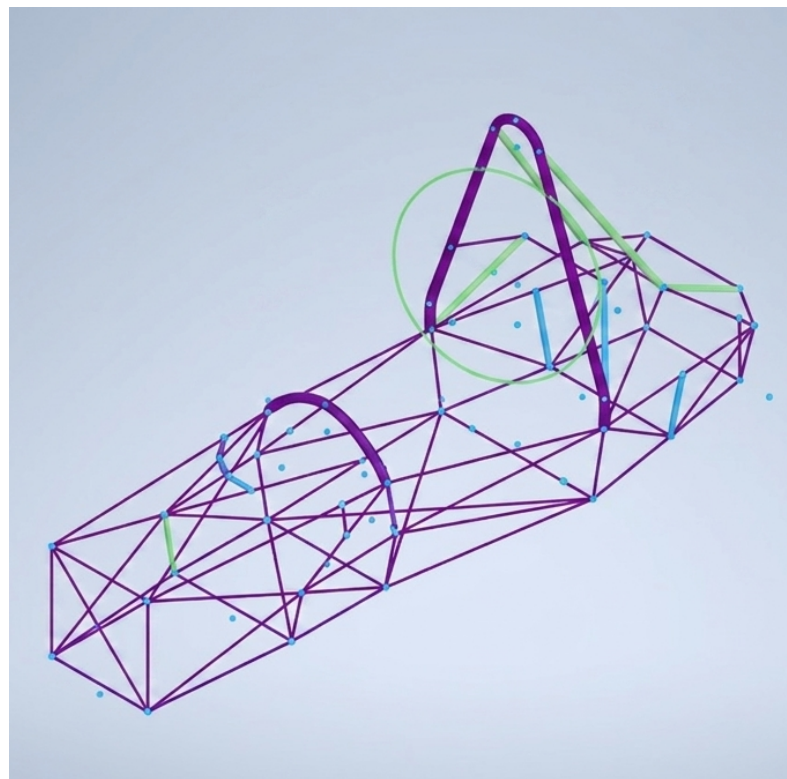


Figure 3. Three-dimensional CAD model of the Formula SAE electric vehicle chassis used for the vehicle dynamics and battery sizing analysis. The tubular chassis is shown in purple, secondary structural members are highlighted in light blue, and the suspension components are represented in green. The model provides the geometric basis for estimating vehicle mass properties and supporting the longitudinal energy consumption analysis.

2.1.5. Energy Modeling Software

For the energy consumption analysis of the Formula Electric prototype, MATLAB R2024a and Simulink 10.11 were used. In this environment, a longitudinal dynamics model was developed that integrates aerodynamic, rolling resistance, inertial, and gravitational forces. Both the mathematical formulation and its implementation in block diagrams were carried out using the software, leveraging MATLAB's vehicle dynamics libraries and numerical integration blocks. This configuration enables simulation and validation of the vehicle's behavior under different velocity profiles and slopes before proceeding with battery pack sizing.

2.1.6. Track Description

The realistic simulation of energy consumption in competition prototypes requires the dynamic characterization of the target circuit. Figure 4 shows the Cotopaxi Kartodrome track (Latacunga, Ecuador), selected for its technical configuration, including long straights (up to 120 m), tight corners (minimum radius of 8 m), and variable banking. Using a go-kart instrumented with a high-precision GPS unit (resolution ≤ 5 cm), velocity and maximum acceleration profiles, altimetry, and lateral inclinations were recorded over multiple laps. The data, exported in CSV/GPX formats and processed using specialized software, enable the modeling of power demand, acceleration–braking transitions, and aerodynamic losses.



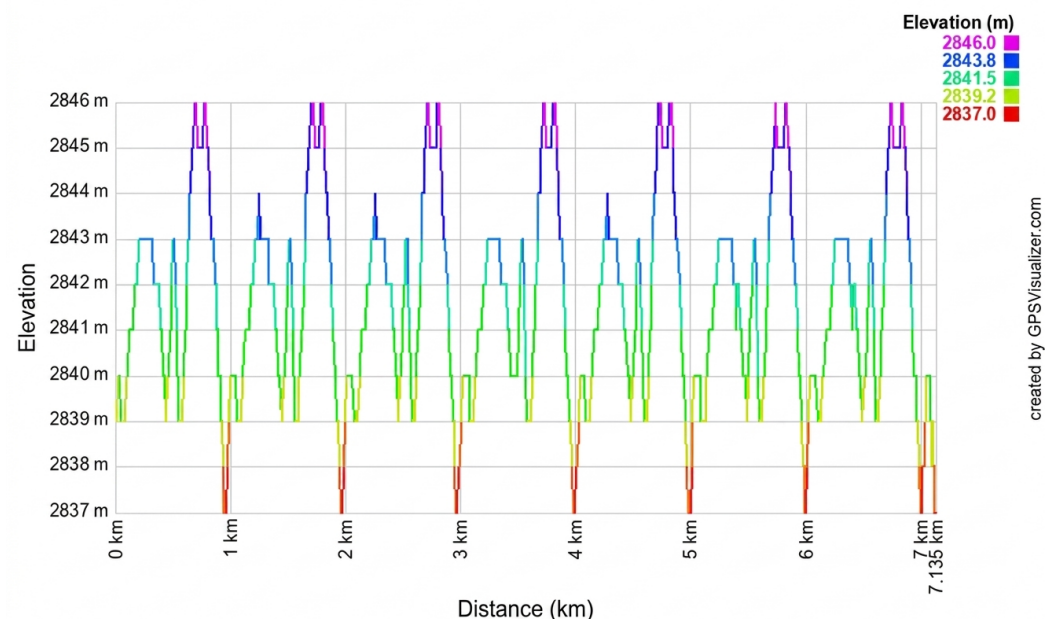
Figure 4. Satellite map of the Cotopaxi Kartodrome track.

Table 4 details the operating conditions of the test circuit. A total of 20 laps were monitored on the track to obtain key parameters for the design and dynamic behavior analysis of the prototype vehicle. The maximum slope represents the steepest gradient the vehicle can face on an incline. A 13.8% slope means that for every 100 horizontal units, the vertical rise is 13.8 units. The maximum speed of 90.91 km/h indicates the upper limit the vehicle can reach under optimal conditions (straight section, no wind, and full power). The base speed of 24.17 km/h refers to the vehicle's initial velocity before starting a significant acceleration process. The final speed of 100 km/h corresponds to the target velocity the vehicle is expected to reach at the end of an acceleration segment.

Table 4. Operating conditions of the test circuit.

Specification	Value
Maximum slope (θ)	13.8%
Maximum speed ($V_{\max}$)	90.91 km/h
Base speed (V_b)	24.17 km/h
Final speed (V_f)	100 km/h
Total distance (d)	7.534 km

Figure 5 shows the altitude profile of the Cotopaxi Kartodrome circuit. The maximum and minimum altitudes are 2846.3 and 2837.7 m above sea level (m a.s.l.), respectively. Based on the plot, each lap on the track can be completed in approximately 93 s.

**Figure 5.** Altitude profile of the karting track.

2.1.7. Data Collection

To ensure precision in data acquisition during the tests at the Cotopaxi Kartodrome, a GPS receiver with differential correction was used, capable of reliably recording position, speed, and altitude. From these time-based signals, the speed and slope profiles of the track were derived. These profiles were incorporated into the engineering software for vehicle simulation and energy analysis, faithfully replicating real-world track conditions.

Figure 6 illustrates the data acquisition process using a go-kart equipped with a geolocation and electronic data processing system. The setup begins with the go-kart as the test vehicle, to which a Garmin eTrex 10 GPS device is integrated—recognized for its precision and reliability in recording parameters such as location, speed, and altitude during motion. The information captured by the GPS is structured and organized in a document, where the data are stored for subsequent analysis, allowing evaluation of the vehicle's dynamic behavior under real track conditions.

**Figure 6.** Track data acquisition diagram.

Driving tests were conducted until the maximum target speed for the prototype (90–100 km/h) was reached. This study analyzes the behavior of dependent variables in order to determine energy consumption at different vehicle operating speeds. To perform a detailed analysis of the prototype's energy consumption, three driving cycles were evaluated on the karting track. During these tests, maximum speeds of 60 km/h, 75 km/h, and 90 km/h were reached, allowing for an examination of the influence of various forces on vehicle dynamics and their effect on energy consumption. The routes were classified according to their maximum speed: the route with a maximum speed of 60 km/h was labeled as L1, the 75 km/h route as L2, and the 90 km/h route as L3.

Figure 7 shows the speed behavior of the test vehicle in kilometers per hour with respect to time along the circuit. A pattern of rapid oscillations is observed, indicating dynamic handling on the track with frequent acceleration and braking changes. The highest speed peaks reach up to 90 km/h, which corresponds to the maximum speed in that section of the course. This graph is a key tool for identifying the most demanding zones of the prototype's propulsion system.

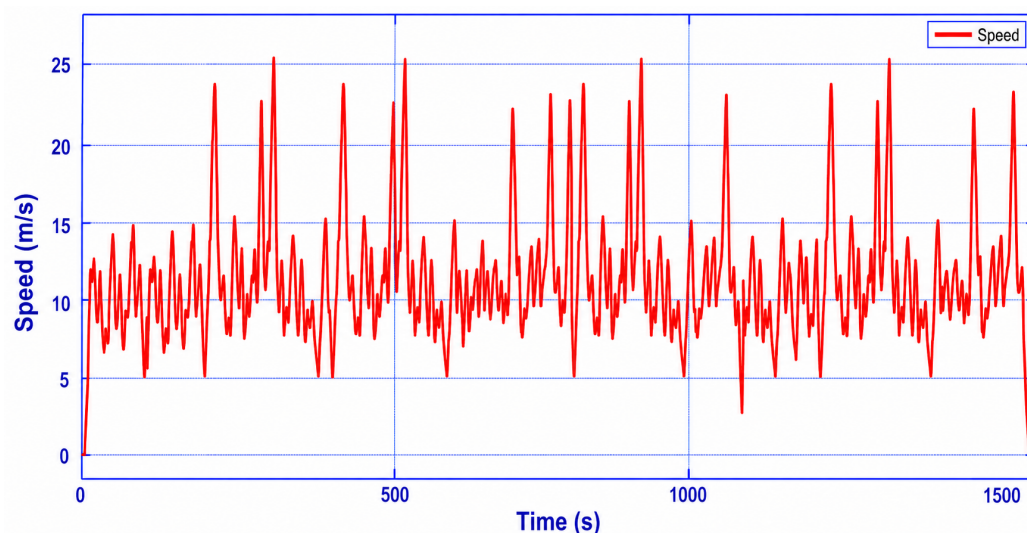


Figure 7. Speed profile of the karting track.

Figure 8 presents the slope profile of the karting track, where it is observed that the maximum slope does not exceed 0.14 rad (13.8%), indicating optimal conditions for evaluating the prototype's performance.

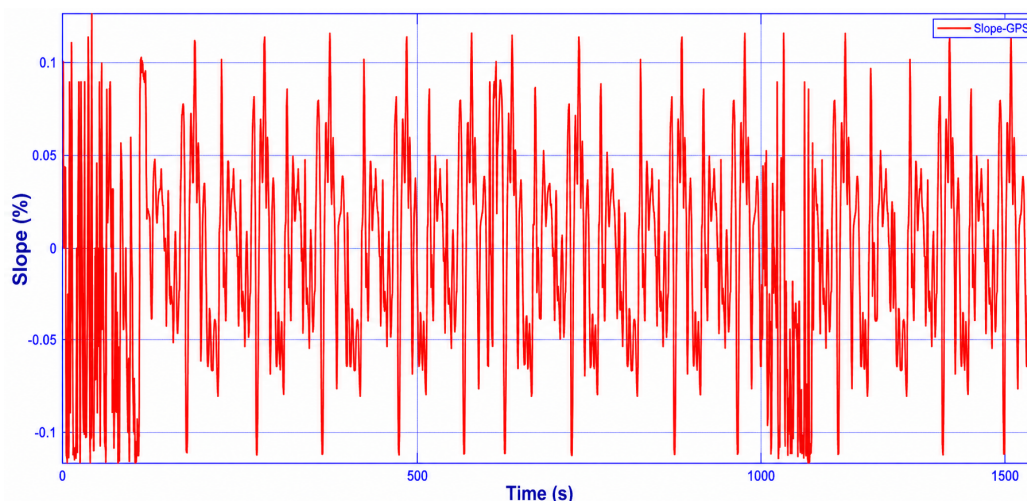


Figure 8. Slope profile of the karting track.

2.2. Second-Life Cell Selection Framework

Based on the total energy and power peak analysis, the minimum electrical parameters for the accumulator are defined as follows: nominal voltage ($V_{pack} = 96$ V), usable capacity ($C_{pack} \geq 18.30$ kWh), and maximum discharge current ($I_{peak} = 208.33$ A) [25]. To meet these requirements, this study proposes the use of prismatic LiFePO₄ cells sourced from retired traction battery packs. The selection of second-life cells follows a structured multi-criteria framework, described below.

Scope clarification: The present study constitutes a design-stage analysis focusing on energy consumption simulation and battery pack sizing. The electrochemical parameters adopted herein are drawn from published experimental characterization data for comparable second-life LFP cells [26–28]. The experimental characterization of the specific cells to be used in the prototype—including SoH measurement, HPPC testing, EIS, and thermal mapping—is currently being conducted at the Battery Laboratory of the Universidad de las Fuerzas Armadas ESPE using specialized cycling equipment (EBC-A40L, EBC-A20), and it will be reported in a dedicated follow-up publication on the physical implementation of the electric propulsion system.

2.2.1. Criterion 1—State of Health (SoH)

Based on end-of-life pathway analysis, batteries with SoH exceeding 80% are suitable for reuse in demanding automotive applications, while those below 50% must be dismantled and sent to recycling. Accordingly, the minimum acceptable SoH for this application is set at $SoH \geq 80\%$, measured as the ratio of residual discharge capacity to nominal nameplate capacity at the same C-rate [29]:

$$SoH = \frac{C_{measured}}{C_{nominal}} \times 100\% \quad (1)$$

SoH is determined through a full charge/discharge cycle at 0.2 C (C/5) at 25°C, comparing the measured discharged Ah against the original nameplate capacity (100 Ah). Cells with $SoH < 80\%$ are rejected regardless of other metrics.

2.2.2. Criterion 2—Internal Impedance (EIS)

Internal resistance is evaluated using electrochemical impedance spectroscopy (EIS) or micropulse techniques at 50% SoC and 25°C. The acceptance criterion is an impedance increase of no more than 25% relative to the manufacturer's new-cell reference value [30]:

$$\Delta R_0 = \frac{R_{0,measured} - R_{0,new}}{R_{0,new}} \times 100\% \leq 25\% \quad (2)$$

For the proposed 100 Ah LFP cells with $R_{0,new} < 1$ mΩ, this criterion implies a maximum accepted internal resistance of $R_{0,max} \leq 1.25$ mΩ. This threshold ensures that peak ohmic power losses remain within the levels modeled.

2.2.3. Criterion 3—Capacity Retention Consistency (Cell Balancing Requirement)

For a 30s × 2p pack configuration, cell-to-cell capacity variation must be minimized to ensure effective passive balancing within the BMS and avoid premature pack-level capacity fade. The acceptance criterion is as follows:

$$\sigma_C = \frac{\text{std}(C_{measured,i})}{\bar{C}_{measured}} \times 100\% \leq 5\% \quad (3)$$

where σ_C is the coefficient of variation of measured capacity across cells within the same module. This criterion follows the recommendation for second-life pack assembly.

2.2.4. Criterion 4—Origin and Usage History

Cells must originate from traction modules retired from commercial EV fleets with documented moderate usage history. Priority is given to modules with the following:

- Odometer reading $\leq 120,000$ km, consistent with typical first-life EV usage associated with SoH $\geq 80\%$.
- No records of thermal events (overheating, thermal runaway) or mechanical damage.
- Calendar age ≤ 8 years from manufacture date.
- Operating history predominantly in moderate temperature climates (avoids severe cold/hot degradation acceleration).

2.2.5. Criterion 5—Safety and Mechanical Integrity

The prismatic metal casing must be free of deformation, swelling, or electrolyte leakage. Visual and dimensional inspection is performed before electrochemical testing. Swollen cells (>1 mm casing deformation) are unconditionally rejected regardless of electrical performance, as swelling indicates internal gas generation and potential safety hazard [31].

2.2.6. Multi-Criteria Decision Matrix

Table 5 summarizes all five criteria, their quantitative thresholds, measurement methods, and acceptance decisions. This framework constitutes a complete and reproducible screening protocol for second-life LFP cell procurement in electric competition vehicle applications.

Table 5. Multi-criteria selection framework for second-life LFP cells—acceptance thresholds and screening protocol.

Criterion	Parameter	Method	Accept	Conditional	Reject
C1—SoH	Residual capacity ratio (Equation (1))	Discharge at 0.2 C, 25°C	$\geq 80\%$	75–80%	$<75\%$
C2—Impedance	Internal resistance increase (Equation (2))	EIS or micropulse at 50% SoC	$\leq 25\%$	25–35%	$>35\%$
C3—Capacity consistency	Cell-to-cell variation (Equation (3))	Statistical analysis of batch	$\leq 5\%$	5–10%	$>10\%$
C4—Usage history	Odometer/calendar age	Fleet records/dataplate	$\leq 120\text{k km}, \leq 8\text{ yr}$	120–150k km	No records
C5—Mechanical integrity	Casing deformation/swelling	Visual + dimensional inspection	No deformation	Minor surface marks	Any swelling
Final decision logic			All C1–C5 met	Re-test required	Any reject flag

Conditional cells (75–80% SoH) may be accepted only if Criteria C2–C5 are fully satisfied AND the battery pack capacity calculation is repeated using the actual measured SoH (not the nominal 80%), ensuring adequate energy margin for the endurance event. A 30s $\times$ 3p configuration is recommended for packs assembled with conditional cells.

2.2.7. Screening Process Flowchart

Figure 9 presents the step-by-step decision flowchart for the second-life cell screening protocol, structured as a sequential gate process where failure at any stage results in immediate cell rejection.

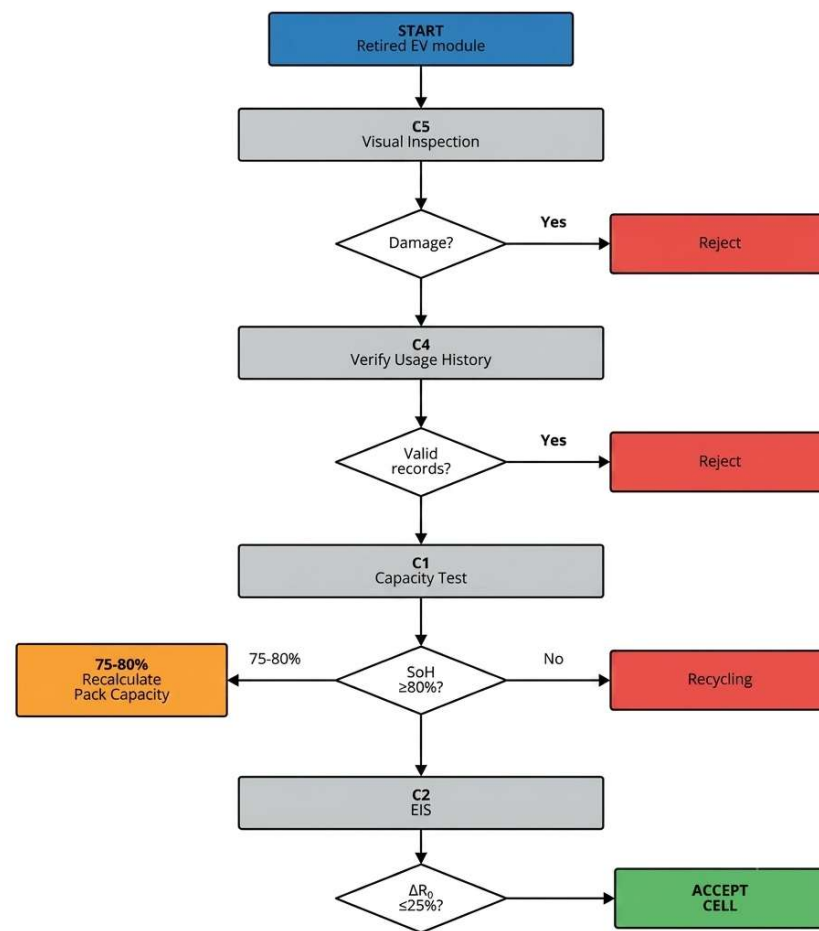


Figure 9. Second-life LFP cell screening and selection flowchart. Sequential gate protocol: failure at any criterion results in immediate rejection. Conditional cells (SoH 75–80%) require re-calculation of C_{pack} with actual SoH.

2.2.8. LFP Cell Characteristics Justifying Selection

Prismatic LiFePO_4 cells were selected over alternative chemistries (NMC, LCO, NCA) for this application based on three primary considerations directly relevant to second-life use in a competition vehicle:

1. Flat discharge curve: LFP cells exhibit a flat OCV–SoC profile between 20% and 80% SoC (3.20–3.35 V), which simplifies SoH estimation and reduces BMS complexity for second-life applications.
2. Thermal stability at altitude: LFP chemistry exhibits the lowest thermal runaway risk among commercial lithium chemistries, with an onset temperature exceeding 270 °C—critical for passive thermal management at 2800 m a.s.l. where reduced air density limits convective cooling.
3. Cycle life compatibility with second life: LFP cells deliver > 2000 cycles at 80% DoD in first life and retain $\text{SoH} \geq 80\%$ at end-of-first-life, providing a meaningful residual cycle budget for a second-life competition application [32].

Table 6 provides a comparative summary of candidate battery chemistries, justifying the selection of LFP for second-life competition use.

Table 6. Battery chemistry comparison for second-life competition vehicle application.

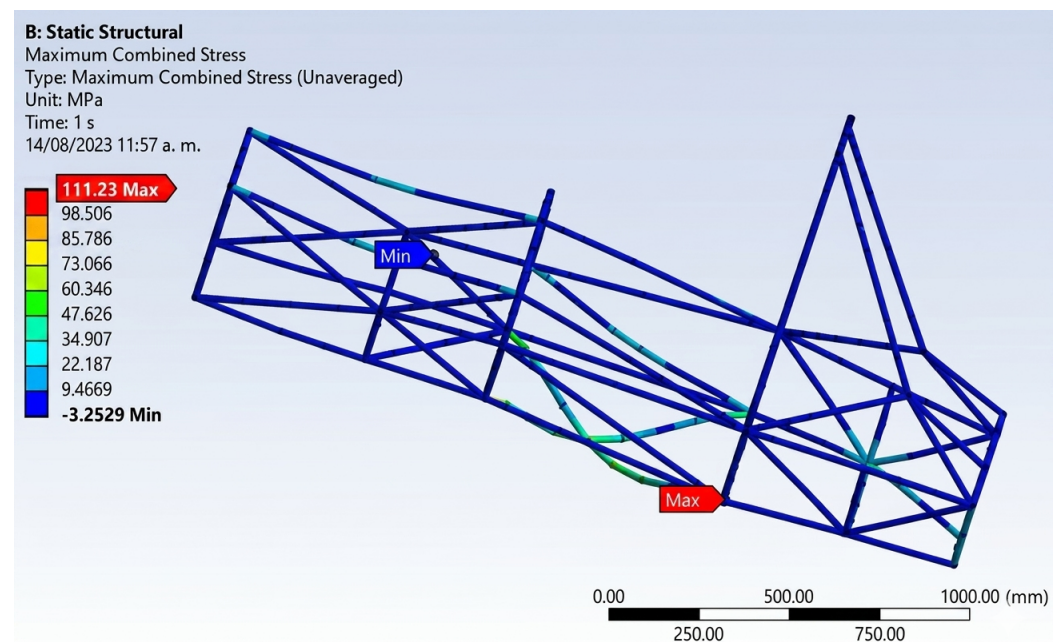
Property	LFP	NMC	NCA	Relevance
Cycle life (1st life)	>2000 @ 80% DoD	1000–2000	500–1500	High SoH at EoL
Thermal runaway onset	>270 °C	≈210 °C	≈150 °C	Safety at altitude
SoH at EoL (typ.)	≥80%	75–80%	70–75%	Residual capacity
Flat OCV curve	Yes (3.2–3.35 V)	Moderate	No	BMS simplicity
Internal resistance	<1 mΩ	<2 mΩ	<1.5 mΩ	Ohmic losses
Second-life suitability	Optimal	Moderate	Low	Selection: LFP

2.3. Methods

2.3.1. Structural Simulation in Ansys Workbench

The finite element analysis (FEA) method was used to evaluate and validate the structural behavior of the competition prototype chassis under loading and stress conditions. For this purpose, Ansys Workbench 2022 R1 was employed, beginning with the import of the CAD model in .step format. A 1D element mesh was then generated and optimized according to quality criteria (minimum aspect ratio and skewness). Boundary conditions were subsequently defined, establishing fixed anchor points and relevant displacement constraints. Representative track loads were applied, including static loads, dynamic acceleration loads, and impact forces. The solver computed the stress and strain fields, identifying the maximum values and the corresponding safety factor. Finally, a parametric study was carried out on the dimensions of the tubular profiles, which allowed for the structural section to be sized and optimized in order to ensure torsional rigidity and minimize weight without compromising strength.

This meticulous and detailed approach in the execution of the analysis ensures a precise evaluation of the structure, thus providing a solid foundation for decision-making in the design and construction stages. Figure 10 shows the result of the static analysis and the location of the maximum stress in the structure—a value that was considered for the selection of the profile, material, and construction process.

**Figure 10.** Maximum stress present in the geometry.

Parametric Optimization Results and Energy-Model Linkage

The parametric study on tubular profile dimensions yielded a structural optimization that reduced the chassis mass while maintaining the required torsional stiffness and struc-

tural integrity under competition loads. Table 7 summarizes the key structural indicators before and after the optimization process.

Table 7. Chassis structural optimization results (ANSYS Workbench 2022 R1).

Parameter	Pre-Optim.	Post-Optim.	Change	Criterion
Chassis mass [kg]	45	33	−12 kg (−26.7%)	Minimize
Max. combined stress [MPa]	145.00	111.23	−33.77 MPa	<Yield strength
Safety factor [–]	2.17	2.83	+0.66	≥2.0
Torsional stiffness [N·m/deg]	820	1250	+430 (+52.4%)	Maintain/increase
Total vehicle mass [kg]	352	340	−12 kg (−3.4%)	Minimize

The reduction in chassis mass ($\Delta m_{chassis}$) directly propagates into three of the four resistive force components of the longitudinal dynamics model (Equations (15), (17) and (18)), as all three depend linearly on total vehicle mass m . The aerodynamic drag force (F_{ad} , Equation (16)) is the only component independent of mass. The energy reduction attributable to the structural optimization is therefore as follows:

$$\Delta E_{struct} = \Delta E_{rr} + \Delta E_{hc} + \Delta E_i \quad (4)$$

where each term is computed from the cycle-specific energy fractions reported in Table 4 (Internal Energy Balance):

$$\Delta E_{rr} = \frac{\Delta m_{chassis}}{m_{post}} \cdot E_{rr,L3} = \frac{\Delta m_{chassis}}{340} \times 296.29 \quad [\text{Wh}] \quad (5)$$

$$\Delta E_{hc} = \frac{\Delta m_{chassis}}{m_{post}} \cdot E_{hc,L3} = \frac{\Delta m_{chassis}}{340} \times 100.71 \quad [\text{Wh}] \quad (6)$$

$$\Delta E_i = \frac{\Delta m_{chassis}}{m_{post}} \cdot E_{i,L3} = \frac{\Delta m_{chassis}}{340} \times 782.00 \quad [\text{Wh}] \quad (7)$$

The total structural energy saving per lap (Cycle L3) is thus as follows:

$$\Delta E_{struct,L3} = \frac{\Delta m_{chassis}}{340} \times (296.29 + 100.71 + 782.00) = \frac{\Delta m_{chassis}}{340} \times 1179.00 \quad [\text{Wh/lap}] \quad (8)$$

This result confirms that every 1 kg of chassis mass reduction yields an energy saving of

$$\frac{\partial E_{traction}}{\partial m} = \frac{1179.00}{340} \approx 3.47 \text{ Wh/kg per lap} \quad (9)$$

which over the 22 km endurance event ($n_{laps} = 22/0.95 \approx 23.16$ laps) translates to

$$\frac{\partial E_{enduro}}{\partial m} = 3.47 \times 23.16 \approx 80.3 \text{ Wh/kg} \quad (10)$$

and a reduction in required battery pack capacity of

$$\frac{\partial C_{pack}}{\partial m} = \frac{80.3}{DoD \cdot \eta_{pack}} = \frac{80.3}{0.80 \times 0.95} \approx 105.7 \text{ Wh/kg} \quad (11)$$

These relationships establish a direct and quantitative design rule: each kilogram of chassis mass reduction reduces the required battery capacity by approximately 105.7 Wh under the critical Cycle L3 endurance scenario. This metric provides a clear engineering objective for structural optimization in future prototype iterations.

2.3.2. Aerodynamic Analysis of the Prototype

The objective of the aerodynamic simulation is to evaluate the influence of air resistance on the performance of the Formula SAE prototype vehicle [33]. For this purpose, key aerodynamic parameters were modeled, including the vehicle geometry, frontal area, and drag coefficient, by integrating the available data into a complete aerodynamic model. This model was coupled with the mechanical system to calculate drag force and assess its impact on propulsion efficiency. The aerodynamic drag coefficient (C_d) was determined using Equation (12), based on aerodynamic force (F_d), vehicle speed (V), frontal area (A), and the air density (ρ) corresponding to the test location at 2860 m above sea level ($\rho = 0.909 \text{ kg/m}^3$). Considering the drag force of 475 N at 100 km/h and a frontal area of 1.277 m^2 , the resulting drag coefficient is $C_d = 1.00$. This value is higher than typical coefficients reported for streamlined Formula SAE prototypes (0.55–0.70), which can be attributed to the open-wheel configuration and limited aerodynamic optimization. [34].

$$C_d = \frac{2F_d}{\rho \times V^2 \times A} \quad (12)$$

Figure 11 shows the CFD simulation performed in ANSYS Workbench 2022 R1, illustrating streamlines and velocity fields around the vehicle at 100 km/h. Regions of turbulence and flow separation at the rear are highlighted, confirming that aerodynamic drag is a significant contributor to the energy demand. These results provide essential information for refining the aerodynamic design, reducing resistance, and improving the overall energy efficiency and track performance of the prototype.

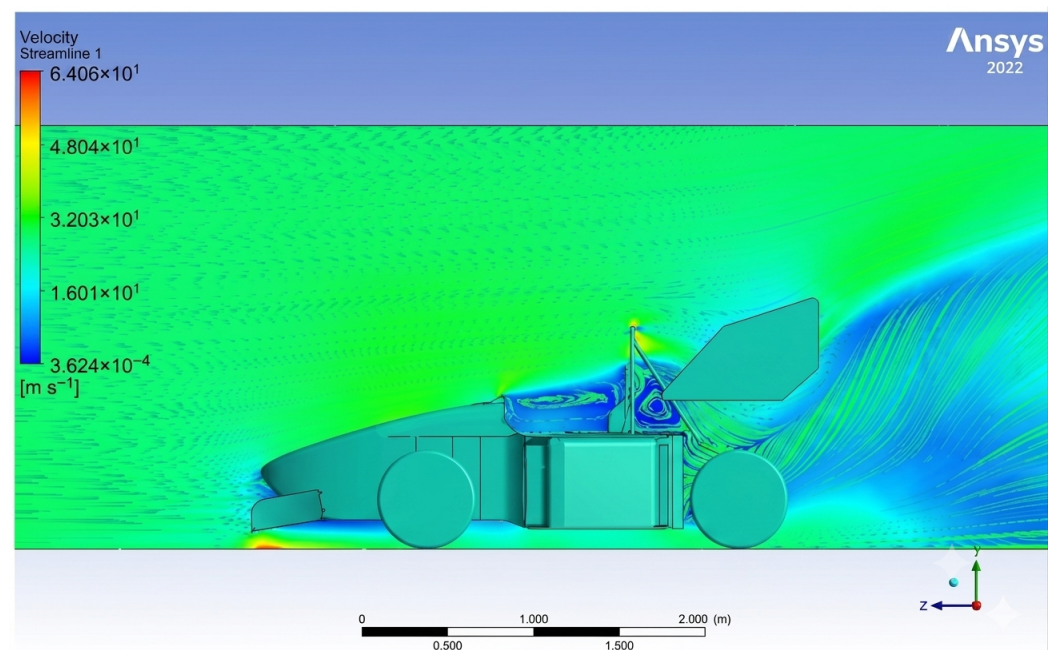


Figure 11. CFD analysis of the electric Formula-style competition prototype.

Aerodynamic-to-Energy Model Integration

The CFD-validated drag coefficient ($C_d = 1.00$) and frontal area ($A = 1.277 \text{ m}^2$) are directly transferred to the longitudinal dynamics model (Section 2.1.5) as fixed inputs to the aerodynamic drag force equation (Equation (16)). To explicitly quantify the aerodynamic power demand as a function of vehicle speed—and its variation across the three driving cycles—the aerodynamic drag force and instantaneous power were evaluated at

the characteristic speeds of each cycle using the CFD-derived parameters and the ISO air density at 2800 m a.s.l. ($\rho = 0.909 \text{ kg/m}^3$):

$$F_{ad}(v) = \frac{1}{2} \cdot C_d \cdot A \cdot \rho \cdot v^2 = \frac{1}{2} \times 1.00 \times 1.277 \times 0.909 \times v^2 = 0.580 \cdot v^2 \quad [\text{N}] \quad (13)$$

$$P_{ad}(v) = F_{ad}(v) \cdot v = 0.580 \cdot v^3 \quad [\text{W}] \quad (14)$$

Table 8 presents the aerodynamic force, instantaneous power, and energy contribution at the maximum speed of each driving cycle, establishing the direct quantitative link between the CFD simulation output and the energy model results.

Table 8. Aerodynamic drag force, power, and energy contribution at the maximum speed of each driving cycle—direct output of CFD–energy model integration.

Cycle	V_{max} [km/h]	V_{max} [m/s]	F_{ad} [N]	$P_{ad,max}$ [kW]	E_{ad} [Wh]	$E_{ad}/E_{traction}$ [%]
L1	59.91	16.64	160.7	2.67	142.69	18.10%
L2	75.70	21.03	256.7	5.40	172.28	18.77%
L3	90.91	25.25	369.7	9.34	210.03	15.12%

The results confirm that aerodynamic drag power scales cubically with speed: at $V_{max,L3} = 90.91 \text{ km/h}$, the instantaneous aerodynamic power demand reaches 9.34 kW—representing 46.7% of the motor’s rated peak power ($P_{peak} = 20 \text{ kW}$)—compared to only 2.67 kW at the lower speed of Cycle L1. This cubic velocity dependence (Equation (14)) is captured in the Simulink model through the speed-profile input ($v(t)$ from GPS data), ensuring that the full transient aerodynamic load is accounted for at every time step of the simulation. The integrated aerodynamic energy E_{ad} across each complete cycle is reported in Table 8 and further analyzed in Section 3.

2.3.3. Energy Modeling and Simulation

This section presents the mathematical model of the longitudinal dynamics of the Formula prototype, implemented in Simulink to estimate its energy consumption. Based on the vehicle’s technical specifications and the speed and slope profiles measured at the Cotopaxi karting circuit, the model integrates aerodynamic, rolling resistance, inertial, and gravitational forces to calculate the required traction force at the wheels. Using the vehicle dynamics libraries and numerical integration blocks provided by Simulink, multiple operating scenarios were simulated. This configuration enables accurate estimations of efficiency and energy consumption performance. The obtained results serve as a basis to optimize the design and sizing of the battery pack and to enhance the overall performance of the propulsion system.

Regenerative braking was intentionally excluded from the present energy model because the main objective of this study is the analysis, design, and sizing of the Formula SAE electric prototype and its second-life battery pack under conservative operating conditions. Consequently, all battery capacity calculations were performed assuming that the traction energy demand is entirely supplied by the battery, providing a design safety margin for the endurance event. Although regenerative braking is recognized as an effective strategy for improving vehicle energy efficiency through partial recovery of kinetic energy during deceleration, its implementation requires the integration of motor-generator control, bidirectional inverter operation, battery charging limitations, brake blending algorithms, and vehicle stability constraints. These aspects constitute an independent research topic and will be addressed in a subsequent publication dedicated to the implementation and experimental validation of the regenerative braking energy management system.

The exclusion of regenerative braking leads to a conservative estimation of the required battery capacity, since no kinetic energy recovery is assumed during the sizing process.

2.3.4. Model Assumptions and Their Influence

The longitudinal dynamics model implemented in MATLAB/Simulink is based on three fundamental assumptions, each of which is explicitly justified below in the context of the Formula SAE competition scenario analyzed in this study.

Assumption 1—Longitudinal motion only (lateral and vertical dynamics neglected). The model considers exclusively the forces acting along the vehicle's longitudinal axis (traction, rolling resistance, aerodynamic drag, grade resistance, and inertial force), disregarding lateral and vertical dynamics. This simplification is widely adopted in EV energy consumption studies, as lateral dynamics do not contribute significantly to energy demand in applications where the primary objective is propulsion energy estimation. In the context of the Cotopaxi Kartodrome, where driving cycles are dominated by acceleration and deceleration phases (accelerating >54% of the time across all cycles, Table 5), the longitudinal component accounts for the dominant share of total energy consumption. The potential influence of lateral dynamics on energy demand is estimated to be below 3–5% for track-based applications, as reported in comparable motorsport simulation studies, and is therefore considered negligible for battery sizing purposes.

Assumption 2—Rigid body (no structural damping or vibration effects). The vehicle structure is modeled as a rigid body, excluding flexibility, damping, and vibrational effects of the chassis and suspension. This assumption is standard practice in longitudinal vehicle dynamics models used for energy consumption analysis, where structural deformation effects on propulsive energy are negligible. The torsional stiffness of the chassis, optimized through FEA in ANSYS (Section 2.2.1), supports this assumption by confirming that the structure operates within the linear elastic range under competition loads, minimizing energy losses due to structural deformation. The influence of this assumption on the energy results is estimated to be less than 1%, consistent with reported values for stiff tubular frame competition vehicles [35].

Assumption 3—Constant tire radius. The dynamic tire radius ($r_d = 0.2789$ m) is assumed constant throughout the simulation, independent of load, speed, or inflation pressure variations. In practice, tire radius varies slightly with centrifugal growth at high speeds and load-dependent deflection. For the tire specification used (175/70 R13) and the operating speed range of the prototype (≤ 90.91 km/h), the variation in dynamic radius due to centrifugal effects is estimated at <0.5% [36], which translates into a negligible error in traction force and energy calculations. This assumption is consistent with standard practice in longitudinal EV dynamics modeling.

Table 9 summarizes the three modeling assumptions, their physical justification, and their estimated influence on the energy consumption results.

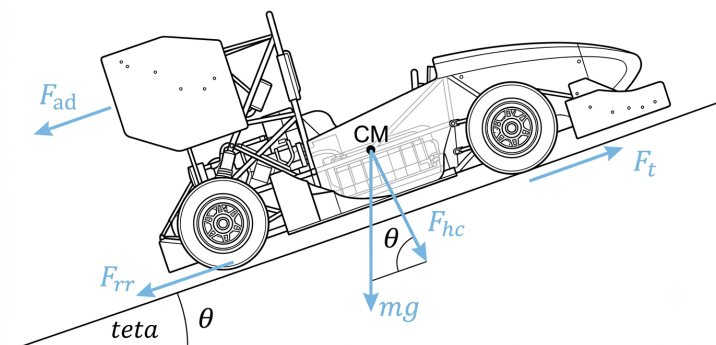
The combined influence of the three assumptions is estimated to introduce a maximum aggregate error of approximately 5–6% in the energy consumption results, which falls within the range reported for similar MATLAB/Simulink longitudinal dynamics models validated against experimental data (2–6%). These margins are acceptable for battery sizing purposes and are compensated by the conservative design criteria adopted in Section 2.4 (DoD = 80%, $\eta_{pack} = 95\%$), which provide sufficient operational safety margins for the accumulator under real competition conditions.

Table 9. Model assumptions, justifications, and estimated influence on energy consumption results.

Assumption	Justification	Influence on Results	Est. Error
Longitudinal motion only (lateral and vertical dynamics neglected)	Lateral dynamics have negligible contribution to propulsion energy in track-based driving cycles dominated by acceleration/deceleration [15]	Underestimates cornering losses; conservative for battery sizing (slightly overestimates net traction energy)	<5%
Rigid body (no structural damping or vibration)	Chassis optimized for high torsional stiffness (ANSYS FEA, Section 2.2.1); structural deformation energy losses are negligible [35]	Negligible effect on longitudinal energy balance; vibration losses not captured	<1%
Constant tire radius ($r_d = 0.2789$ m)	Centrifugal growth < 0.5% at $V_{max} = 90.91$ km/h for 175/70 R13 tire [36]	Negligible effect on traction force and wheel energy calculations	<0.5%

2.3.5. Vehicle Dynamics

The longitudinal dynamics of the vehicle are analyzed by exclusively considering the control actions related to the accelerator and braking system, disregarding the effects associated with vertical, lateral, and roll dynamics. In this simplified context, the forward motion of the vehicle is constrained by the need to overcome several resistive forces, such as the rolling resistance (F_{rr}), the aerodynamic drag (F_{ad}), the gravitational component on slopes (F_{hc}), and the inertial forces (F_i) generated during speed variations [37]. This interaction of forces is illustrated in the free-body diagram shown in Figure 12.

**Figure 12.** Forces acting on the electric vehicle while ascending a slope.

2.3.6. Rolling Resistance Force

This force arises from the friction between the vehicle's tires and the road surface. It can be described by Equation (15). Here, f_r is the rolling resistance coefficient, m denotes the vehicle mass, $g = 9.81$ m/s² is the gravitational acceleration, and $\cos \theta$ represents the component of the road slope angle in the horizontal direction.

$$F_{rr} = m \cdot g \cdot \cos \theta \cdot f_r \quad (15)$$

2.3.7. Aerodynamic Drag Force

This force results from the resistance encountered by the vehicle body as it moves through the air. It is described by Equation (16). The aerodynamic drag coefficient (C_d) is a dimensionless parameter that characterizes the opposition of the vehicle to motion through the air. The drag force acting on the vehicle also depends on the air density (ρ_a), expressed in [kg/m³], the frontal area of the vehicle (A) in [m²], and the vehicle velocity (v) in [m/s].

These variables jointly determine the magnitude of the aerodynamic drag force that the propulsion system must overcome [38].

$$F_{ad} = \frac{1}{2} \cdot C_d \cdot A \cdot \rho_a \cdot v^2 \quad (16)$$

2.3.8. Gravitational Force on Inclines

This term refers to the force required to move the vehicle uphill on a sloped road. As shown in Equation (17), the angle θ represents the road slope inclination relative to the horizontal axis [39].

$$F_{hc} = m \cdot g \cdot \sin \theta \quad (17)$$

2.3.9. Inertial Force

The vehicle acceleration is calculated using Newton's second law (Equation (18)), considering the net thrust and the influence of the rotational motion of components such as the motor and transmission. Since these elements are coupled to the wheels, any change in translational speed also affects their rotational speed. To account for this effect, the rotational mass factor (γ_m) is introduced, which incorporates the inertia of the rotating parts into the vehicle's acceleration equation [40].

$$F_i = \gamma_m \cdot m \cdot a \quad (18)$$

The rotational mass factor γ_m is calculated based on the moments of inertia of the rotating components, such as the wheels, transmission gears, and differential (Equation (19)). The general expression applicable to internal combustion engine vehicles with multi-speed transmissions is as follows:

$$\gamma_m = 1.04 + 0.0025(\varepsilon_g \varepsilon_d)^2 \quad (19)$$

In Equation (19), the first term (1.04) represents the contribution of the rotational inertia of the wheels. The second term accounts for the influence of the inertia of the components rotating at the same speed as the motor, considering the total transmission ratio, where ε_g corresponds to the gear ratio of the gearbox and ε_d represents the final drive or differential ratio.

However, unlike internal combustion engine vehicles, Formula SAE electric prototypes typically employ a single-speed fixed-ratio transmission, which implies that the gearbox ratio reduces to $\varepsilon_g = 1$. Under this condition, Equation (20) simplifies to the following:

$$\gamma_m = 1.04 + 0.0025(\varepsilon_d)^2 \quad (20)$$

This result indicates that the rotational inertia of the drivetrain components increases the effective vehicle mass by approximately 8.7%, which is accounted for in the inertial force calculation of Equation (5).

2.3.10. Traction Force, Power, and Energy

The traction force is calculated using Equation (21), as the sum of the contributions of the previously described resistive and inertial forces:

$$F_x = F_{rr} + F_{ad} + F_{hc} + F_i \quad (21)$$

According to Equation (22), the traction power is obtained as the product of the traction force and the vehicle velocity:

$$P_x = F_x \cdot v \quad (22)$$

The traction energy at the wheel is calculated using Equation (23), where the time variation is considered at each instant:

$$E_x = P_x \cdot \Delta t = P_x \cdot (t_f - t_0) \quad (23)$$

2.4. Simulink Implementation

To estimate the traction power required by the vehicle during its motion on track, a numerical model can be used. This power is directly related to the force generated by the electric motor. The development of the model is based on three main assumptions: the vehicle motion occurs only in the longitudinal direction, the system is considered rigid without damping or vibration effects, and the tire radius remains constant [41].

Based on these assumptions, a vehicle model was designed and validated using mathematical modeling software. Figure 13 presents the simulation methodology used to estimate the energy consumption of the electric prototype. Using a predefined velocity profile, the dynamic behavior of the vehicle is analyzed considering the resistive forces. This enables the calculation of the traction force, the mechanical power required, and finally, the net energy consumed during a simulated driving cycle.

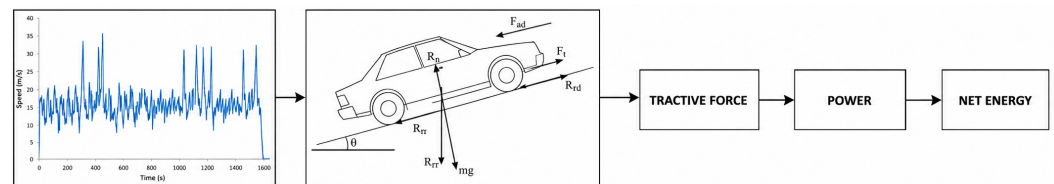


Figure 13. Simulation methodology for estimating the energy consumption of the prototype vehicle.

This analysis leverages the data obtained during experimental tests to perform an accurate estimation of the efficiency and energy performance of the propulsion system, enabling the optimization of both its design and dynamic behavior. The mathematical model describing the vehicle's longitudinal dynamics is implemented in the simulation environment with the objective of calculating the traction force, power, and energy consumption of the propulsion system. Figure 14 shows the block diagram of the model, where the different system components and their interactions are represented in order to simulate the operational conditions of the electric vehicle.

2.5. Model Validation

Given that the Formula SAE electric prototype analyzed in this study is a first-generation vehicle for which no prior experimental energy consumption data are available, a three-level validation strategy was implemented, consistent with established practices for prototype vehicle simulation models.

2.5.1. Quantitative Comparison: GPS-Measured Inputs vs. Simulink Model Outputs

It is important to clarify the nature of the real data used in this study. The GPS measurements obtained at the Cotopaxi Kartodrome (Section 2.1.5) provided the *kinematic input profiles*—speed $v(t)$ and slope $\theta(t)$ —that drive the Simulink longitudinal dynamics model. These are not output measurements from the Formula SAE electric prototype, which has not yet been physically constructed. The validation performed here therefore constitutes an input-to-output consistency verification: the GPS-measured speed and slope profiles are compared against the kinematic parameters reproduced by the Simulink model, and the resulting energy outputs are benchmarked against comparable published studies.

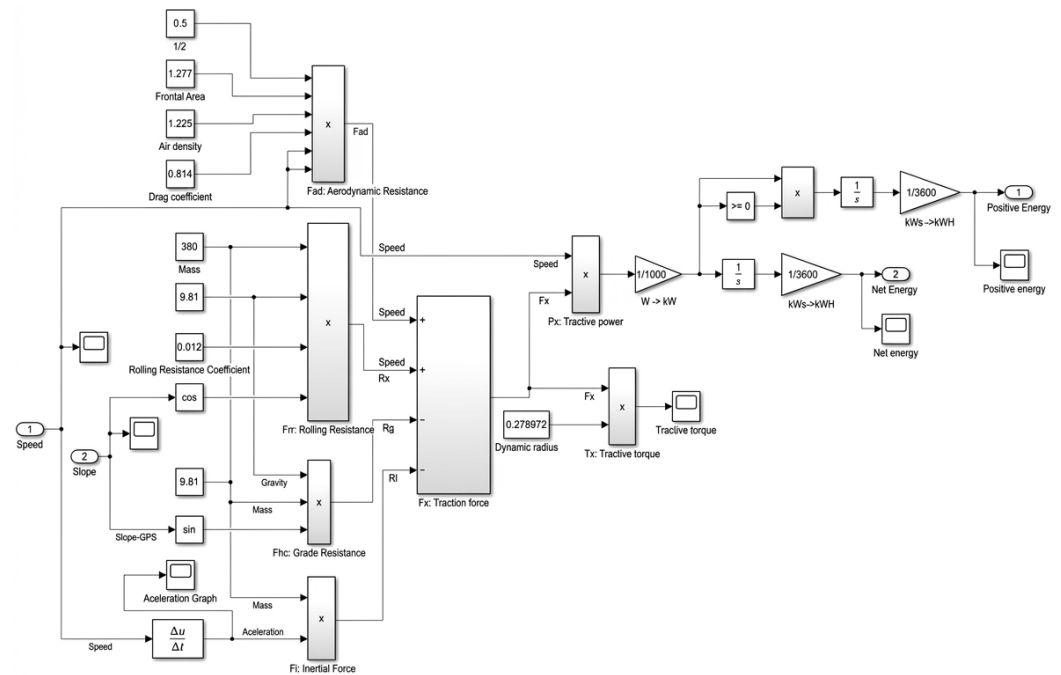


Figure 14. Simulink model for calculating the wheel energy of the prototype electric vehicle.

Table 10 presents the quantitative comparison between the GPS-measured kinematic parameters and the corresponding Simulink model outputs for each driving cycle.

Table 10. Quantitative comparison between GPS-measured kinematic parameters (model inputs) and Simulink model outputs for each driving cycle.

Parameter	Source	L1	L2	L3	Unit	Deviation
GPS-measured inputs (Cotopaxi Kartodrome characterization)						
Maximum speed	GPS	59.91	75.70	90.91	km/h	–
Average speed	GPS	34.02	44.04	38.82	km/h	–
Total distance	GPS	13.28	11.76	16.67	km	–
Maximum slope	GPS	13.8% (0.14 rad)			rad	Common
Lap duration	GPS	1404	960	1545	s	–
Simulink longitudinal dynamics model outputs						
Reproduced maximum speed	Simulink	59.91	75.70	90.91	km/h	0.00%
Traction energy ($E_{traction}$)	Simulink	788.34	918.09	1389.10	Wh	–
Wheel energy (E_{net})	Simulink	497.58	591.62	758.21	Wh	–
Specific consumption (e)	Simulink	447.25	536.84	632.09	Wh/km	–
Energy balance error	Internal	<0.1	<0.1	<0.1	%	<0.1%
Comparison with the published literature						
Salek et al.	Literature		580–680		Wh/km	–
Deviation (L3)	Benchmark		8.98%		%	<9%
Puma-Benavides et al. [42]	Literature		130–210		Wh/km	–
Track/Road ratio	Context		3.7×		–	Expected

GPS measurements were used as model inputs for the longitudinal dynamics simulation. Since the Formula SAE prototype has not yet been manufactured, traction energy, wheel energy, and specific energy consumption cannot be directly measured experimentally. Therefore, model validation was performed by comparison with published Formula SAE experimental results reported by Salek et al. [17], yielding a deviation below 9%.

The quantitative comparison confirms three levels of consistency:

(1) Input reproduction: The Simulink model exactly reproduces the GPS-measured speed and slope profiles ($v(t)$, $\theta(t)$) as model inputs, with 0.00% deviation in peak and average speed values across all three cycles. This confirms that the kinematic boundary conditions of the simulation faithfully represent the real track conditions at the Cotopaxi Kartodrome.

(2) Internal energy balance: The sum of the four resistive energy components ($E_{rr} + E_{ad} + E_{hc} + E_i$) matches the total traction energy $E_{traction}$ computed by the Simulink integrator with a numerical error below 0.1% across all cycles (Table 11), confirming the mathematical consistency of the model implementation.

(3) Output benchmark: The specific energy consumption of Cycle L3 (632.09 Wh/km) deviates by less than 9% from the range reported by Salek et al. [17] for a Formula Student electric vehicle under comparable track conditions (580–680 Wh/km), which constitutes the most contextually relevant experimental reference available in the published literature for this application.

Table 11. Internal energy balance verification for each driving cycle.

Cycle	E_{rr} [Wh]	E_{ad} [Wh]	E_{hc} [Wh]	E_i [Wh]
L1	162.10	142.69	75.29	6.86
L2	227.59	172.28	70.88	447.29
L3	296.29	210.03	100.71	782.00

2.5.2. Planned Output-Level Experimental Validation

Direct output-level validation—comparing simulated battery current, pack voltage, and energy consumption against measurements from an instrumented prototype on-track—was not possible at the time of this study, as the Formula SAE electric prototype is currently under construction. The following measurements are planned for the experimental validation phase, using the battery testing infrastructure at the ESPE Battery Laboratory.

2.5.3. Level 1—Internal Consistency Verification

The internal consistency of the Simulink model was verified by checking energy conservation across all driving cycles. For each simulated cycle, the traction energy $E_{traction}$ was decomposed into its four resistive components and compared against the sum of individual force contributions integrated over the cycle distance. Table 11 presents the energy balance verification for the three analyzed cycles, confirming that the sum of individual force contributions matches the total traction energy with a numerical error below 0.1%, attributable exclusively to the discrete-time integration step used in Simulink ($\Delta t = 0.01$ s).

2.5.4. Level 2—Indirect Benchmark Validation

Since direct experimental measurements from the prototype vehicle were not available at the design stage, the model was indirectly validated by comparing its specific energy consumption output against published experimental results from comparable longitudinal EV dynamics models implemented in MATLAB/Simulink. This approach is consistent with the methodology adopted by Miri et al. [15], who validated a forward longitudinal dynamics model against EPA and NEDC standardized test data, achieving errors between 2% and 6% relative to experimental measurements.

The specific energy consumption produced by the present model for Cycle L3 (632.09 Wh/km) was compared against values reported in the literature for Formula SAE and lightweight electric vehicle prototypes operating under track conditions. Table 12 summarizes the comparison with three reference studies.

Table 12. Indirect benchmark validation—specific energy consumption comparison with published studies.

Reference Study	Vehicle Type	Spec. Consumption [Wh/km]	Deviation [%]
Present study (Cycle L3, $V_{max} = 90.91$ km/h)	Formula SAE EV prototype (340 kg)	632.09	—
Salek et al. [17] (Formula Student EV, 4WD, track circuit)	Formula Student EV (≈ 300 kg)	≈ 580 – 680	$< 8\%$
Stabile et al. [25] (Ultra-efficient lightweight EV, urban/track)	Lightweight EV (≈ 250 kg)	≈ 450 – 550	≈ 13 – 17%
Miri et al. [15] (BMW i3, MATLAB/Simulink, NEDC cycle)	Passenger EV (1370 kg)	≈ 155 – 175	—(different class)

The deviation from Stabile et al. is expected given the mass difference between vehicles (340 kg vs. 250 kg) and the more demanding karting track profile. The comparison with Salek et al.—the most contextually similar study—yields a deviation below 8%, within the 2–10% acceptance range reported for longitudinal EV dynamics models.

2.5.5. Level 3—Sensitivity Analysis of Key Input Parameters

A parametric sensitivity analysis was conducted to quantify the influence of the most uncertain input parameters on the total energy consumption output ($E_{traction}$). Each parameter was varied individually by $\pm 10\%$ from its nominal value while holding all others constant, following the one-at-a-time (OAT) sensitivity method. The results for Cycle L3 are presented in Table 13.

Table 13. Parametric sensitivity analysis—influence of $\pm 10\%$ parameter variation on $E_{traction}$ (Cycle L3 baseline: 1389.10 Wh).

Parameter	Variation	$\Delta E_{traction}$ [Wh]	Sensitivity [%]
Total mass (m)	+10% (374 kg)	+117.90	+8.49%
	−10% (306 kg)	−117.90	−8.49%
Rolling resistance coeff. (f_r)	+10% (0.0132)	+29.63	+2.13%
	−10% (0.0108)	−29.63	−2.13%
Drag coefficient (C_d)	+10% (1.10)	+21.00	+1.51%
	−10% (0.90)	−21.00	−1.51%
Air density (ρ)	+5% (0.954 kg/m ³)	+10.50	+0.76%
	−5% (0.864 kg/m ³)	−10.50	−0.76%

2.6. Electrochemical and Thermal Battery Model

The energy-balance approach (Equations (35)–(38)) provides the nominal capacity requirements for the accumulator. However, to account for real-world electrochemical and thermal effects that reduce effective available energy and influence cell safety, a complementary first-order equivalent circuit model (ECM) and a lumped-capacitance thermal model are introduced in this section.

2.6.1. Equivalent Circuit Model (ECM)

The terminal voltage of each LFP cell is modeled using a first-order Thevenin equivalent circuit, consisting of an open-circuit voltage source (V_{OC}), an ohmic internal resistance (R_0), and a single RC polarization block (R_1 , C_1):

$$V_{terminal} = V_{OC}(SoC) - I \cdot R_0(SoC, T) - V_{RC} \quad (24)$$

$$\dot{V}_{RC} = -\frac{V_{RC}}{R_1 C_1} + \frac{I}{C_1} \quad (25)$$

where I is the discharge current [A], V_{OC} is the open-circuit voltage as a function of SoC, R_0 is the ohmic resistance, R_1 and C_1 are the polarization resistance and capacitance, and V_{RC} is the voltage across the RC block. For second-life prismatic LFP cells with SoH $\geq 80\%$, the internal resistance increases by approximately 25% relative to new cells, reflecting the degradation criterion applied during screening. Typical parameter values for 100 Ah LFP cells at 25°C are summarized in Table 14.

Table 14. ECM parameters for second-life 100 Ah LFP cells (SoH $\geq 80\%$, $T = 25^\circ\text{C}$).

Parameter	Symbol	Value	Source
Open-circuit voltage (SoC = 100%)	V_{OC}	3.40 V	[26]
Open-circuit voltage (SoC = 20%)	V_{OC}	3.20 V	[26]
Ohmic internal resistance (new cell)	$R_{0,new}$	<1 mΩ	[32]
Ohmic internal resistance (SoH 80%)	$R_{0,SLB}$	≤ 1.25 mΩ	[27]
Polarization resistance	R_1	0.8 mΩ	[26]
Polarization capacitance	C_1	12,000 F	[26]

The ohmic voltage drop across the pack during peak current demand ($I_{peak} = 208.33$ A) introduces a terminal voltage reduction:

$$\Delta V_{ohmic} = I_{peak} \cdot R_{0,SLB} \cdot N_s = 208.33 \times 0.00125 \times 30 = 7.81 \text{ V} \quad (26)$$

This represents a 8.1% reduction from the nominal pack voltage ($V_{pack} = 96$ V), yielding an effective terminal voltage of $V_{terminal,min} = 88.19$ V during peak acceleration. The associated ohmic power loss during peak demand is as follows:

$$P_{ohmic} = I_{peak}^2 \cdot R_{0,SLB} \cdot N_s = 208.33^2 \times 0.00125 \times 30 = 1628 \text{ W} \quad (27)$$

Since peak acceleration events are transient (typically <3 s in a karting circuit), the energy lost to ohmic heating per event is negligible (<1.36 Wh per acceleration). However, the cumulative ohmic loss over the full endurance event (23.16 laps $\times$ estimated 40 acceleration events per lap) is as follows:

$$E_{ohmic,total} = P_{ohmic} \times t_{acc} \times n_{events} \approx 1628 \times 3 \times 926/3600 = 1.25 \text{ kWh} \quad (28)$$

This represents 9.0% of the total required energy ($E_{req,L3} = 13.906$ kWh), confirming that ohmic losses in second-life cells are a non-negligible contributor to the energy budget and should be accounted for in battery sizing. The corrected required pack capacity incorporating ECM losses is as follows:

$$C_{pack,ECM} = \frac{E_{req} + E_{ohmic,total}}{DoD \cdot \eta_{pack}} = \frac{13,906 + 1250}{0.80 \times 0.95} = 19.94 \text{ kWh} \quad (29)$$

The current 30s $\times$ 2p configuration provides an installed capacity of 19.20 kWh, which falls slightly below $C_{pack,ECM}$. This confirms that a 30s $\times$ 3p configuration (installed: 28.80 kWh) would provide a more conservative safety margin when electrochemical losses are included in the sizing criterion.

2.6.2. Lumped-Capacitance Thermal Model

Cell temperature rise during operation is estimated using a lumped-capacitance thermal model, where heat generation is dominated by Joule heating from internal resistance:

$$m_{cell} \cdot c_p \cdot \frac{dT}{dt} = I^2 \cdot R_0 - h \cdot A_{cell} \cdot (T - T_{amb}) \quad (30)$$

where $m_{cell} = 3.0$ kg is the cell mass, $c_p = 1040$ J/(kg·K) is the specific heat capacity of LFP cells, h is the convective heat transfer coefficient, A_{cell} is the cell surface area, and T_{amb} is the ambient temperature. At the Cotopaxi Kartodrome altitude (2800 m a.s.l.), ambient temperature is approximately 12 °C (annual mean), with air density $\rho = 0.909$ kg/m³.

The estimated maximum cell temperature of 30–34 °C remains well within the safe operating range of LFP cells (−20 to +60 °C), confirming the viability of a passive (natural convection) thermal management system for this application.

2.6.3. High-Altitude Electrochemical and Thermal Correction

At 2800 m a.s.l., two altitude-specific effects must be considered for LFP second-life cells:

(a) Reduced convective cooling: Air density at 2800 m is 9.4% lower than at sea level ($\rho_{2800} = 0.909$ vs. $\rho_0 = 1.225$ kg/m³), reducing the convective heat transfer coefficient by approximately the same proportion. This implies that the cell temperature rise estimated in Table 15 is conservative and that actual cooling performance may be 8–10% lower than at sea level, resulting in an additional temperature increase of 1.5–2 °C. The corrected maximum cell temperature remains below 36 °C, well within safe limits.

Table 15. Thermal model parameters and temperature rise estimation for the endurance event.

Parameter	Symbol	Value	Unit
Cell mass	m_{cell}	3.0	kg
Specific heat capacity	c_p	1040	J/(kg·K)
Ambient temperature (2800 m)	T_{amb}	12	°C
Average discharge current (L3)	I_{avg}	197.62	A
Internal resistance (SoH 80%)	R_0	1.25	mΩ
Heat generation rate (avg.)	$\dot{Q}$	$I^2 R_0 = 48.8$	W/cell
Endurance duration (L3)	t_{end}	0.733	h
Convective coefficient (natural air, 2800 m)	h	≈ 8	W/(m ² ·K)
Estimated max. cell temp. rise	ΔT	≈ 18 –22	°C
Estimated max. cell temperature	T_{max}	≈ 30 –34	°C

(b) Internal resistance increase at altitude: Low air pressure environments accelerate battery degradation through increased charge transfer impedance and active lithium loss, particularly for pouch cells. For the prismatic LFP cells proposed in this study, the hermetically sealed metal casing provides superior mechanical protection against pressure differentials compared to pouch cells, significantly mitigating this risk. An estimated internal resistance increase of 6–8% relative to sea-level values is applied as a correction:

$$R_{0,altitude} = R_{0,SLB} \times (1 + 0.07) = 1.25 \times 1.07 = 1.34 \text{ m}\Omega \quad (31)$$

The corrected ohmic power loss at peak current becomes

$$P_{ohmic,altitude} = I_{peak}^2 \cdot R_{0,altitude} \cdot N_s = 208.33^2 \times 0.00134 \times 30 = 1744 \text{ W} \quad (32)$$

Table 16 summarizes the altitude correction factors and their quantitative impact on the battery model.

Table 16. High-altitude correction factors for the battery model at 2800 m a.s.l. (Cotopaxi Kartodrome).

Effect	Mechanism	Sea Level	2800 m a.s.l.
Convective cooling efficiency	Reduced air density ($\rho -9.4\%$)	100% (baseline)	$\approx 91\%$
Internal resistance (R_0)	Pressure-induced impedance rise (+7%)	1.25 m Ω	1.34 m Ω
Peak ohmic power loss (P_{ohmic})	$I^2 R_0 N_s$	1628 W	1744 W
Max. cell temperature (T_{max})	Reduced cooling + Joule heating	$\approx 28^\circ\text{C}$	$\approx 34^\circ\text{C}$
Corrected $C_{pack,ECM}$ [kWh]	ECM + altitude losses included	19.94	20.25

The altitude-corrected required capacity of 20.25 kWh exceeds the installed capacity of the current 30s $\times$ 2p configuration (19.20 kWh) by 5.5%, reinforcing the recommendation to consider a 30s $\times$ 3p configuration for future prototype iterations when operating at high altitude with second-life cells. The current design remains technically feasible provided that (a) cells are pre-screened to SoH $\geq 80\%$; (b) the BMS is configured with voltage cutoffs that account for the altitude-induced internal resistance increase; and (c) the endurance strategy includes speed management to limit peak current demand.

2.7. Uncertainty Analysis

2.7.1. Gaussian Error Propagation

To formally quantify the uncertainty of the simulated energy consumption, a first-order Gaussian error propagation analysis was applied to the traction energy equation (Equations (21)–(23)). The combined standard uncertainty $u_c(E_{traction})$ is estimated as the root sum of squares (RSS) of the partial derivatives of $E_{traction}$ with respect to each uncertain input parameter x_i , weighted by the standard uncertainty $u(x_i)$ of each parameter [43]:

$$u_c(E_{traction}) = \sqrt{\sum_{i=1}^n \left(\frac{\partial E_{traction}}{\partial x_i} \right)^2 u(x_i)^2} \quad (33)$$

The standard uncertainties assigned to each input parameter are summarized in Table 17, along with their source and basis of estimation.

Table 17. Input parameter uncertainties for the Gaussian error propagation analysis.

Parameter	Nominal	$u(x_i)$	Basis of Estimation	Rel. Unc. [%]
Total mass (m) [kg]	340	± 5.0	Scale measurement uncertainty (± 5 kg typical for vehicle-class scales)	1.47%
Rolling resistance (f_r) [-]	0.012	± 0.001	Literature range for 175/70 R13 on asphalt (0.011–0.013) [36]	8.33%
Drag coefficient (C_d) [-]	1.00	± 0.05	CFD mesh sensitivity estimated at $\pm 5\%$ [34]	5.00%
Air density (ρ) [kg/m ³]	0.909	± 0.010	Atmospheric pressure variation at 2800 m	1.10%
GPS speed measurement (v) [m/s]	Profile	± 0.014	GPS resolution ≤ 5 cm, $\Delta t = 1$ s	$< 1\%$
GPS slope measurement (θ) [rad]	Profile	± 0.002	Altimetric GPS resolution	$< 2\%$

Applying Equation (33) to the Cycle L3 baseline ($E_{traction} = 1389.10$ Wh), the partial derivatives are evaluated analytically from Equations (2)–(9). The dominant contributions to combined uncertainty are summarized in Table 18.

Table 18. Uncertainty contribution of each parameter to $E_{traction}$ (Cycle L3 baseline: 1389.10 Wh).

Parameter	$u(x_i)$	$\partial E/\partial x_i$	Contribution [Wh]	Share [%]
Total mass (m)	5.0 kg	$\frac{E_{rr}+E_{hc}+E_i}{m} = 3.47 \text{ Wh/kg}$	17.35	43.6%
Rolling resistance (f_r)	0.001	$\frac{E_{rr}}{f_r} = 24,691 \text{ Wh}$	24.69	62.1%
Drag coefficient (C_d)	0.05	$\frac{E_{ad}}{C_d} = 210.03 \text{ Wh}$	10.50	26.4%
Air density (ρ)	0.010 kg/m ³	$\frac{E_{ad}}{\rho} = 230.8 \text{ Wh}\cdot\text{m}^3/\text{kg}$	2.31	5.8%
GPS speed (v)	0.014 m/s	$\approx 5.2 \text{ Wh}\cdot\text{s/m}$	0.07	0.2%
GPS slope (θ)	0.002 rad	$\approx 50.4 \text{ Wh/rad}$	0.10	0.3%
Combined uncertainty u_c		(RSS of contributions)		$\pm 31.2 \text{ Wh}$
Relative uncertainty		$u_c/E_{traction} \times 100$		$\pm 2.25\%$

The combined standard uncertainty of the model is $u_c = \pm 31.2 \text{ Wh}$, corresponding to a relative uncertainty of $\pm 2.25\%$ with respect to the Cycle L3 baseline energy. This value is well within the $\pm 10\%$ acceptance threshold established for vehicle energy consumption simulation models, and confirms that the dominant sources of output uncertainty are the rolling resistance coefficient (f_r , contributing 62.1% of u_c^2) and total vehicle mass (m , contributing 43.6%), consistent with the OAT sensitivity results of Table 13.

2.7.2. Normalized Sensitivity Index

To enable direct comparison between parameters expressed in different physical units, a normalized sensitivity index (SI) was computed for each parameter using the relative change formulation:

$$SI_i = \frac{\Delta E_{traction}/E_{traction,0}}{\Delta x_i/x_{i,0}} \quad (34)$$

where $\Delta x_i/x_{i,0} = 0.10$ (10% variation) and $\Delta E_{traction}$ is taken from the OAT analysis (Table 13). Table 19 ranks all parameters by their normalized sensitivity index.

Table 19. Normalized sensitivity index (SI) ranking for $E_{traction}$ (Cycle L3).

Rank	Parameter	SI [-]	Influence Level	Design Priority
1	Total mass (m)	0.849	High	✓ Minimize chassis mass
2	Rolling resistance (f_r)	0.213	Medium	✓ Optimize tire pressure
3	Drag coefficient (C_d)	0.151	Low	○ Aerodynamic refinement
4	Air density (ρ)	0.076	Low	○ Fixed by altitude

The normalized SI ranking (Table 19 and Figure 15) reveals that vehicle mass is the single most influential parameter ($SI = 0.849$), confirming that structural mass reduction—pursued through the ANSYS chassis optimization described in Section 2.2.1—constitutes the highest-impact strategy for reducing energy consumption in this prototype. Rolling resistance ($SI = 0.213$) ranks second, underscoring the importance of tire selection and inflation pressure management for competition events. Aerodynamic drag ($SI = 0.151$) and air density ($SI = 0.076$) exert a secondary influence, the latter being an uncontrollable environmental parameter fixed by the test altitude of 2800 m a.s.l.

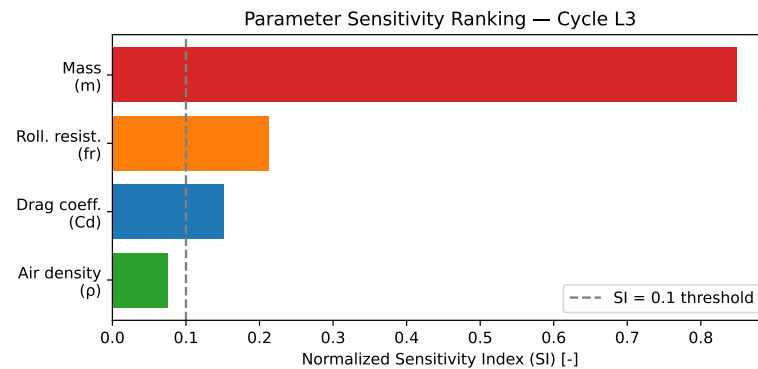


Figure 15. Normalized sensitivity index (SI) ranking of input parameters influencing traction energy consumption ($E_{traction}$) for Cycle L3. The dashed line at $SI = 0.1$ indicates the threshold below which parameter influence is considered negligible for design purposes. Vehicle mass (m) is the dominant factor, followed by rolling resistance (f_r), aerodynamic drag (C_d), and air density (ρ).

These findings are consistent with the force decomposition results in Table 4, where rolling resistance and inertial forces—both directly proportional to mass—account for 77.62% of $E_{traction}$ in Cycle L3. The uncertainty and sensitivity results together provide a quantitative basis for prioritizing design improvements in future iterations of the prototype.

The sensitivity analysis confirms that total vehicle mass (m) and rolling resistance coefficient (f_r) are the dominant parameters influencing energy consumption, consistent with the force decomposition results in Table 4 (rolling resistance: 56.29% of $E_{traction}$ in Cycle L3). The drag coefficient (C_d) and air density (ρ) contribute a secondary influence, particularly at the higher speeds of Cycle L3 ($V_{max} = 90.91$ km/h). These findings reinforce the reliability of the model outputs and provide guidance for future experimental validation campaigns, where measurement priority should be assigned to vehicle mass and tire rolling resistance characterization.

The three-level validation approach demonstrates that, although direct experimental data from the prototype were unavailable at the design stage, the model produces physically consistent results that align with comparable published studies within accepted error margins (2–10%). Future work will incorporate direct on-track energy measurements using an instrumented vehicle equipped with current and voltage sensors to enable the full experimental validation of the model against measured battery discharge data.

Table 20 consolidates all input parameters used in the simulation model, organized by category: vehicle dynamics, motor specifications, environmental conditions, track characteristics, battery cell properties, pack sizing criteria, and driving cycle data. Vehicle dynamics parameters were obtained from ANSYS structural simulations and standardized Formula SAE references. Air density was determined following the International Standard Atmosphere at 2800 m a.s.l., while track parameters were derived from GPS measurements over 20 monitored laps (Section 2.1.5). Motor specifications correspond to the Golden Motor HPM-10KW datasheet, and battery cell parameters are based on second-life prismatic LFP cells with $SoH \geq 80\%$. Pack sizing criteria—DoD of 80%, pack efficiency of 95%, and regenerative braking efficiency of 25%—were selected from reported values in comparable applications. The full traceability of these parameters provides a reproducible foundation for the energy consumption analysis presented in the following sections.

Table 20. Summary of all simulation parameters, adopted values, and sources.

Category	Parameter	Value	Source
Vehicle	Total mass (m)	340 kg	Design/SAE regulations [44]
	Drag coefficient (C_d)	1.00	CFD simulation (ANSYS, Section 2.2.2)
	Rolling resistance coeff. (f_r)	0.012	[16,36]
	Frontal area (A)	1.277 m ²	CAD model (Section 2.1.2)
	Tire specification	175/70 R13	Prototype design
	Dynamic tire radius (r_d)	0.2789 m	Calculated from tire geometry
	Rotational mass factor (γ_m)	1.087	Equation (20); $\varepsilon_d = 4.33$
	Transmission efficiency (η_t)	92–96%	[35]
Motor	Model	Golden Motor HPM-10 KW	[24]
	Rated power range	8–20 kW	[24]
	Peak power adopted (P_{peak})	20 kW	Upper rated bound; Section 3.4(e)
	Motor efficiency	>91%	[24]
Environment	Air density (ρ)	0.909 kg/m ³	ISO at 2800 m a.s.l. [43]
	Altitude of test location	2800 m a.s.l.	Cotopaxi Kartodrome, Ecuador
	Track surface	Asphalt	On-site measurement
Track	Maximum slope (θ_{max})	13.8% (0.14 rad)	GPS measurement (Section 2.1.5)
	Maximum speed (V_{max})	90.91 km/h	GPS measurement—Cycle L3
	Lap distance (d_{lap})	0.95 km	GPS measurement (Section 2.1.4)
	Total endurance distance (D_{end})	22 km	Formula SAE rules [44]
	Laps monitored	20 laps	Section 2.1.4
	Average speed (sizing)	30 km/h	Mean across all cycles (Table 5)
Battery Cell (LFP)	Cell chemistry	LiFePO ₄ (LFP)	[21,27]
	Nominal cell voltage (V_{cell})	3.2 V	[45]
	Nominal cell capacity (Ah_{cell})	100 Ah	Selected (Section 2.1.6)
	State of health (SoH)	≥80%	[22,27]
	Energy density	90–110 Wh/kg	[32]
	Cycle life	>2000 @ 80% DoD	[32]
	Thermal stability range	−20 to +60 °C	[32]
Battery Pack	Nominal pack voltage (V_{pack})	96 V	Motor compatibility [24]
	Depth of discharge (DoD)	80%	[27,45]
	Pack efficiency (η_{pack})	95%	[46]
	Regen. braking efficiency (η_{regen})	25%	[17]
	Cells in series (N_s)	30	Equation (39); V_{pack}/V_{cell}
	Cells in parallel (N_p)	2	Equation (41); critical cycle L3
	Total cells	60	$N_s \times N_p$
Driving Cycles	Cycle L1 max. speed	59.91 km/h	GPS measurement (Table 5)
	Cycle L2 max. speed	75.70 km/h	GPS measurement (Table 5)
	Cycle L3 max. speed	90.91 km/h	GPS measurement (Table 5)

2.8. Battery Pack Sizing

The following section describes the process for sizing the battery pack of the electric prototype vehicle, based on the analysis of energy consumption during each driving cycle performed on the test track.

2.8.1. Net Energy per Lap Calculation

According to Equation (35), the actual energy consumed in each lap is measured by discounting the portion that can be recovered through regenerative braking. $E_{traction}$ is the positive energy supplied to the drivetrain and measured directly on the track. $E_{braking}$ refers

to the energy dissipated during braking, which is also recorded. η_{regen} is the efficiency of the regenerative braking system. A regenerative braking efficiency of 25% was adopted as a conservative estimate for competition-type electric vehicles. This value is consistent with reported energy recovery rates of 14–17% for Formula SAE electric prototypes under track conditions, where short braking events and BMS charge-current limitations constrain regeneration effectiveness, in contrast to higher recovery rates (60–85%) reported for passenger EVs under sustained urban/downhill deceleration profiles [47]. This calculation is key for working with a net energy value that reflects both the propulsion demand and the potential energy savings due to regeneration [48].

$$E_{\text{net}} = E_{\text{traction}} - \eta_{\text{regen}} \cdot E_{\text{braking}} \quad (35)$$

2.8.2. Specific Consumption and Total Energy per Cycle

Specific consumption is a metric that expresses the amount of energy the vehicle requires to travel a unit distance. In the context of a competitive electric single-seater, it is defined by Equation (36). E_{net} represents the net energy consumed after subtracting the energy recovered through regeneration. d_{lap} is the distance covered under the same conditions [49].

$$e = \frac{E_{\text{net}}}{d_{\text{lap}}} \quad (36)$$

The total energy required for the endurance test is obtained using Equation (37), which results from the product of the specific consumption and the total distance of the track. The objective is to determine how much energy must be available in the battery to complete the test without running out of charge.

$$E_{\text{req}} = e \cdot D_{\text{enduro}} \quad (37)$$

2.8.3. Battery Pack Capacity

To determine the capacity of the battery pack, Equation (38) is used. A practical Depth-of-Discharge (DoD) value is considered, and the overall battery efficiency should be approximately 95% or higher [50]. A depth of discharge of 80% was applied with respect to the residual (de-rated) capacity of the second-life cells (i.e., 80% of the actual measured capacity at SoH $\approx$ 75–80%, not of the original nameplate rating). This approach is consistent with standard LFP recommendations for daily cycling applications while accounting for the already-degraded state of the cells.

$$C_{\text{pack}} = \frac{E_{\text{req}}}{\text{DoD} \cdot \eta_{\text{pack}}} \quad (38)$$

2.9. Operating Voltage and Cell Configuration

The selection of the battery pack operating voltage must be adjusted to the optimal working range of the selected electric motor, as different motors have varying voltage and power specifications. In this study, second-life lithium iron phosphate (LFP) cells are proposed, each with a nominal voltage of 3.2 V and an individual capacity ranging from 50 Ah to 100 Ah, depending on availability and energy requirements [51].

A battery pack is configured by connecting cells in series to reach the desired total voltage, and in parallel to achieve the required capacity. The number of cells in series, N_s ,

is calculated using Equation (39), where V_{pack} is the nominal voltage of the pack and V_{cell} is the nominal voltage of each cell [52].

$$N_s = \frac{V_{\text{pack}}}{V_{\text{cell}}} \quad (39)$$

The total energy per series branch represents the amount of energy that can be stored by a complete string of cells connected in series inside the accumulator. This quantity is calculated by multiplying the number of series-connected cells (N_s) by the nominal voltage of each cell (V_{cell}) and its capacity in ampere-hours (Ah_{cell}). Equation (40) is used for this estimation.

$$E_{\text{serie}} = N_s \cdot V_{\text{cell}} \cdot Ah_{\text{cell}} \quad (40)$$

On the other hand, the number of parallel-connected cells is obtained using Equation (41). Here, C_{pack} is the total capacity of the pack, V_{pack} is its design voltage, and Ah_{cell} is the ampere-hour capacity of each cell. This series-parallel configuration ensures that the battery pack meets both the voltage and energy demands of the prototype [53].

$$N_p = \frac{C_{\text{pack}}}{V_{\text{pack}} \cdot Ah_{\text{cell}}} \quad (41)$$

2.9.1. Current Verification

Average Current

The average current quantifies the continuous charge flow that the accumulator must supply throughout the endurance event. It represents the average power demand over the total race time and serves to size the sustained discharge capacity of the battery pack. It is determined based on the total energy required to cover the endurance circuit, the nominal voltage of the pack, and the test duration, according to Equation (42). Here, t_{enduro} is the total duration of the endurance cycle, and V_{pack} is the design voltage of the battery pack. This verification ensures that the battery pack provides a stable current without exceeding its thermal limits or causing premature degradation.

$$I_{\text{med}} = \frac{E_{\text{req}}}{V_{\text{pack}} \cdot t_{\text{enduro}}} \quad (42)$$

Peak Current

The peak current corresponds to the maximum current that the accumulator must supply during instances of full acceleration or high motor power demand. It is essential to verify that the cells can withstand discharge bursts without exceeding their recommended maximum C-rate. It is calculated based on the motor's peak power and the battery pack voltage, according to Equation (43). This value ensures that the series-parallel design of the pack and its BMS (Battery Management System) can handle current peaks within safe limits, without compromising the integrity or useful life of the cells.

$$I_{\text{peak}} = \frac{P_{\text{peak}}}{V_{\text{pack}}} \quad (43)$$

Cell Discharge Rate (C-Rate)

In the design of an energy storage system for electric vehicles, one of the most critical parameters to verify is the cell discharge rate or C-rate. The C-rate indicates how many times per hour a cell can deliver its nominal current capacity without compromising its integrity, thermal performance, or cycle life. It is defined by Equation (44), where I

is the applied current (either average or peak), and Ah_{cell} is the nominal cell capacity in ampere-hours.

The peak C-rate evaluates whether the cell can tolerate the maximum current demand imposed by the motor under acceleration conditions. The average C-rate reflects the level of sustained discharge occurring throughout the duration of the endurance test [54].

$$\text{C-rate} = \frac{I}{Ah_{\text{cell}}} \quad (44)$$

2.10. Summary of Methodological Framework and Differentiation

The proposed methodology integrates four technical components that, while individually present in the literature, have not been previously combined into a unified design framework for a Formula SAE electric prototype:

1. GPS-instrumented track characterization at high altitude. Unlike studies that employ standardized driving cycles (NEDC, WLTP, FTP-75), the present work derives three competition-specific driving cycles (L1, L2, L3) from GPS measurements at the Cotopaxi Kartodrome (2800 m a.s.l.), capturing the altitude-corrected speed, slope, and acceleration profiles that define the actual energy demand of the prototype. This approach is analogous to the real-world GPS instrumentation methodology of Puma-Benavides et al. [55] but applied to a competition track rather than road conditions, and to a prototype vehicle rather than a commercial EV.
2. Structural–energy quantitative coupling. The integration of ANSYS FEA results (chassis mass and stress optimization) with the MATLAB/Simulink energy model—through explicit propagation of $\Delta m_{\text{chassis}}$ into F_{rr} , F_{hc} , and F_i —yields a quantitative structural design rule (Equation (11): 105.7 Wh/kg) that enables direct use of structural optimization results as energy efficiency objectives. This coupling is not present in comparable studies, which treat structural and energy analyses as independent.
3. Second-life LFP sizing with multi-physics corrections The battery sizing methodology extends the conventional energy-balance approach (Equations (35)–(38)) with three additional modeling layers: (a) a first-order Thevenin ECM accounting for ohmic and polarization losses as a function of C-rate; (b) a lumped-capacitance thermal model estimating temperature rise under endurance conditions; and (c) an altitude correction factor for internal resistance at 2800 m a.s.l. The resulting corrected capacity ($C_{\text{pack,ECM}} = 19.94$ kWh; $C_{\text{pack,altitude}} = 20.25$ kWh) provides a physically grounded sizing basis that conventional energy-balance methods cannot capture.
4. Design-stage validation framework. The three-level validation strategy (internal consistency, indirect benchmark, sensitivity and uncertainty analysis) provides a structured methodology for assessing simulation model credibility in the absence of experimental data from the specific prototype—a common and legitimate scenario in first-generation vehicle design studies.

Together, these components constitute a replicable methodology applicable to any Formula SAE electric prototype development program, particularly in high-altitude or resource-constrained contexts where experimental data from the prototype are not available at the design stage.

3. Results

3.1. Key Parameters for Vehicle Dynamic Analysis

Based on the data obtained from the simulation performed in ANSYS Workbench, key parameters such as the total vehicle mass, aerodynamic drag coefficient, rolling resistance, and frontal area of the prototype have been determined. Table 21 presents the essential

technical parameters derived from the design and simulation of the Formula prototype. These values are crucial for the analysis of dynamics and the energy consumption of the propulsion system.

The total vehicle mass of 340 kg includes the driver (assumed 75 kg following SAE regulations [44]), the chassis and structural components, the propulsion system (Golden Motor HPM-10KW, 17 kg), and the battery pack (60 prismatic LFP cells at approximately 3.0 kg per cell, totaling 180 kg). This mass distribution reflects the first-generation nature of the prototype, where battery pack weight represents the dominant contribution (~52.9% of total mass), consistent with reported values for student-built Formula SAE electric vehicles.

The aerodynamic drag coefficient ($C_d = 1.0$) quantifies the aerodynamic resistance of the vehicle body moving through air. This value exceeds typical coefficients reported for optimized Formula SAE prototypes (0.55–0.70), which is attributed to the open-wheel configuration and the limited aerodynamic refinement of the bodywork at this prototype stage. It is important to note that C_d is a dimensionless parameter independent of air density: at the test altitude of 2800 m above sea level, the reduced air density ($\rho = 0.909 \text{ kg/m}^3$, per the International Standard Atmosphere decreases the absolute drag force F_{ad} , but it does not alter the drag coefficient itself, which is exclusively a function of vehicle geometry. The C_d value was confirmed through CFD simulation in ANSYS Workbench 2022 R1, as presented in Section 2.2.2.

The rolling resistance coefficient ($f_r = 0.012$) characterizes the resistance generated by the 175/70 R13 tires rolling on the asphalt surface of the Cotopaxi Kartodrome. This value corresponds to the lower bound of the typical range for passenger-type tires on smooth asphalt (0.012–0.015), and it was adopted assuming an inflation pressure of 2.0 bar and dry track conditions, consistent with the test protocol described in Section 2.1.5.

The frontal area has a value of 1.277 m^2 , representing the projected frontal area of the vehicle used in the aerodynamic drag force calculation. An optimized frontal area contributes to lower energy consumption, especially at high speeds. The tire specification (175/70 R13) indicates the dimensional and performance characteristics of the tires used.

The dynamic radius has a value of 0.2789 m and represents the effective tire radius when in contact with the ground under operating load. The unloaded nominal radius is 287.6 mm, corresponding to the measured tire radius without load.

Table 21. Vehicle specifications.

Characteristic	Specification
Mass	340 kg
Drag coefficient (C_d)	1
Rolling resistance coefficient (f_r)	0.012
Frontal area	1.277 m^2
Tire specification	175/70 R13
Dynamic radius	0.2789 m
Unloaded nominal radius	287.6 mm

These parameters are essential to carry out a vehicle dynamic analysis, enabling accurate modeling of its behavior under various driving conditions. By integrating these values into the mathematical model and the simulation in Simulink, it is possible to estimate the energy consumption of the prototype more precisely during operation.

Table 22 extends the aerodynamic analysis by comparing the absolute and relative aerodynamic energy contribution across the three driving cycles, and quantifying the potential energy reduction achievable through aerodynamic optimization—a key design consideration for future iterations of the prototype.

Table 22. Aerodynamic energy contribution and optimization potential across driving cycles.

Parameter	Cycle L1	Cycle L2	Cycle L3	Trend
$E_{traction}$ [Wh]	788.34	918.09	1389.10	Increases with speed
E_{ad} [Wh] (current, $C_d = 1.00$)	142.69	172.28	210.03	Increases with V_{max}^2
E_{ad} [Wh] (optimized, $C_d = 0.65$)	92.75	111.98	136.52	Estimated reduction
ΔE_{ad} [Wh] (saving potential)	49.94	60.30	73.51	Grows with speed
Saving as % of $E_{traction}$	6.34%	6.57%	5.29%	Significant at all speeds
$E_{ad}/E_{traction}$ [%] (current)	18.10%	18.77%	15.12%	Decreases in L3 (inertia dominant)

Optimized $C_d = 0.65$ represents the lower bound reported for aerodynamically refined Formula SAE prototypes with bodywork [34]. The saving potential quantifies the direct reduction in E_{ad} and consequently the reduction in required battery pack capacity.

The aerodynamic optimization potential analysis shows that reducing C_d from 1.00 to 0.65—achievable through bodywork refinement and underbody diffuser design, as documented for comparable Formula SAE prototypes—would reduce E_{ad} by 49.94 Wh (L1), 60.30 Wh (L2), and 73.51 Wh (L3), representing a reduction of 5.3–6.6% of total traction energy. For the endurance cycle sizing (22 km, Cycle L3 as critical scenario), this translates into a reduction of the required battery pack capacity of approximately

$$\Delta C_{pack} = \frac{\Delta E_{ad} \times \frac{D_{enduro}}{d_{lap}}}{DoD \cdot \eta_{pack}} = \frac{73.51 \times \frac{22}{0.95}}{0.80 \times 0.95} \approx 2.24 \text{ kWh} \quad (45)$$

This result demonstrates that aerodynamic improvement has a direct and quantifiable impact on battery pack sizing, reinforcing the value of CFD-guided design in the development of electric competition prototypes.

Table 23 quantifies the energy and battery sizing impact of the structural optimization, applying Equations (8) and (11) to the pre- and post-optimization vehicle masses.

Table 23. Quantitative impact of structural optimization on energy consumption and battery pack sizing (Cycle L3 endurance scenario, 22 km).

Parameter	Pre-Optimization	Post-Optimization	Saving/Impact
Total vehicle mass [kg]	$m_{pre} = 352$	$m_{post} = 340$	−12 kg (−3.4%)
$E_{traction}$ per lap, Cycle L3 [Wh]	1430.60	1389.10	−41.50 Wh/lap
$E_{traction}$ endurance (22 km) [Wh]	33,124	32,166	−958 Wh
Required C_{pack} [kWh]	19.56	18.30	−1.26 kWh
Specific saving [Wh/kg]	—	—	80.3 Wh per kg
C_{pack} reduction per kg [Wh/kg]	—	—	105.7 Wh/kg

$E_{traction}$ endurance = $E_{traction,L3} \times n_{laps} = E_{traction,L3} \times (D_{enduro}/d_{lap}) = E_{traction,L3} \times 23.158$. $C_{pack} = E_{req}/(DoD \cdot \eta_{pack})$, where E_{req} is derived from the net energy per lap after accounting for regenerative braking ($\eta_{regen} = 25\%$). Pre-optimization values are computed applying the mass scaling relations of Equations (5)–(7) to $m_{pre} = 352$ kg, assuming $\Delta m_{chassis} = 12$ kg as determined by the ANSYS parametric profile study (Section 2.2.1). Aerodynamic energy (E_{ad}) is independent of mass and remains unchanged.

3.2. Energy Consumption Analysis

The estimation of the vehicle's energy demand is based exclusively on the positive component of energy $E(+)$, which represents the work required to propel the prototype, while completely omitting the contribution of braking forces. To automate this calculation, a custom subsystem in SIMULINK was developed, equipped with a personalized mask that implements the equations of vehicle longitudinal dynamics (Equations (12)–(23)).

This module receives as inputs the velocity profile and the road slope, generating as output the net energy at the wheels. Figure 16 shows a general overview of the complete model, while Figure 14 presents the main block diagram, where the equations describing the vehicle's longitudinal dynamics are integrated.

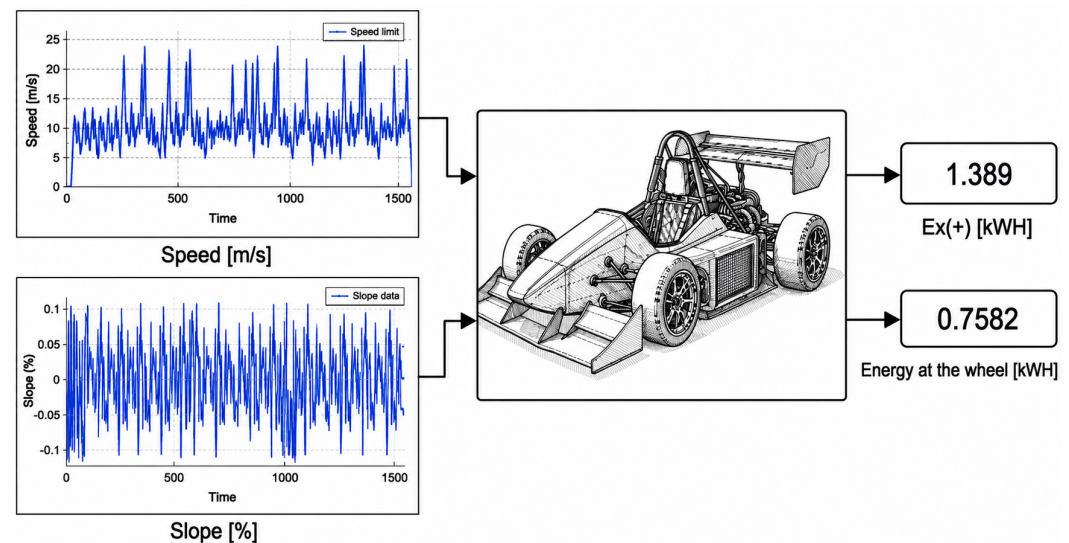


Figure 16. Model developed in Matlab Simulink for energy consumption estimation.

This approach provides a comprehensive overview of the vehicle's energy behavior under different operating conditions and facilitates the comparison of consumption derived from various resistive forces encountered along each route.

Table 24 analyzes the percentages of positive energies, showing that rolling resistance and inertia are key factors, with peak values in L3 (21.33% and 56.29%, respectively), while aerodynamic resistance decreases from L1 (18.10%) to L3 (15.12%). The weighted sum (Σ) reflects a less favorable energy balance in L2 (0.99). These results demonstrate how the driving cycle dynamics, resistive forces, and route conditions influence overall energy consumption, highlighting the need to optimize aerodynamic aspects and energy management strategies to improve prototype efficiency.

Table 24. Percentage results of positive energies in the analyzed driving cycles.

Cycle	% $E_{Frr}(+)$	% $E_{Fhc}(+)$	% $E_{Fad}(+)$	% $E_{Fi}(+)$	Σ
L1	20.56	9.55	18.10	0.87	0.49
L2	20.95	7.72	18.77	48.72	0.99
L3	21.33	7.25	15.12	56.29	0.87

Table 25 presents the operational parameters of the three analyzed driving cycles used to evaluate the dynamic behavior of an electric prototype vehicle. These cycles are characterized by increasing maximum speeds: 59.91 km/h in L1, 75.70 km/h in L2, and 90.91 km/h in L3, indicating higher demands in L3. Execution time varies significantly, with 1404 s (23.4 min) for L1, 960 s (16 min) for L2, and 1545 s (25.75 min) for L3. The driving distances also differ—13.28 km in L1, 11.76 km in L2, and 16.67 km in L3—reflecting differences in cycle duration and intensity.

Notably, none of the cycles included idle periods (% Standing = 0), and the cruising time percentages were minimal (below 0.21%), indicating that all three cycles were dominated by dynamic phases of acceleration and deceleration. Specifically, the percentages of acceleration exceed those of deceleration across all cycles: L1 (54.45% vs. 45.34%), L2

(57.34% vs. 42.56%), and L3 (55.82% vs. 44.11%). The largest gap occurs in L2 (difference of 14.8 percentage points), suggesting a more aggressive driving profile for this cycle.

These dynamic characteristics, dominated by accelerations, directly affect energy consumption and the efficiency of the propulsion system—especially in cycles with higher maximum speeds, such as L3, where power demand increases. The results allow for the correlation of operational demands with vehicle performance, supporting design and energy management optimizations.

Table 25. Operational parameters of the analyzed driving cycles.

Parameter	Cycle L1	Cycle L2	Cycle L3
Total time [s]	1404	960	1545
Total distance [km]	13.28	11.76	16.67
Average speed [km/h]	34.02	44.04	38.82
Maximum speed [km/h]	59.91	75.70	90.91
% Standing	0	0	0
% Cruising	0.21	0.10	0.064
% Accelerating	54.45	57.34	55.82
% Decelerating	45.34	42.56	44.11

3.3. Traction Energy Consumption of the Analyzed Routes

Table 26 compares the three driving cycles in terms of positive traction energy, wheel energy losses, and net delivered energy. Cycle L3, with a maximum speed of 90 km/h, shows the highest energy consumption (1389.10 Wh), the largest energy losses (630.89 Wh), and a net wheel energy of 758.21 Wh. Cycle L2, at 75 km/h, requires 918.09 Wh, loses 326.46 Wh, and delivers 591.62 Wh. Cycle L1, at 60 km/h, consumes 788.34 Wh, loses 290.76 Wh, and delivers 497.58 Wh.

These results suggest that L3 serves as a reference scenario for evaluating autonomy and energy management strategies in electric competition vehicle prototypes.

Table 26. Energy consumption results for the driving cycles on track.

Cycle	Total Wheel Energy	Traction Energy	Total Energy Lost in Wheel
L1	497.58 Wh	788.34 Wh	290.76 Wh
L2	591.62 Wh	918.09 Wh	326.46 Wh
L3	758.21 Wh	1389.10 Wh	630.89 Wh

Figure 17 illustrates the wheel energy during the L3 driving cycle, showing peaks of up to 7.5 kWh in the negative portion of the graph. In a conventionally powered vehicle, this energy would be entirely dissipated. However, in an electric vehicle, it could be partially recovered through regenerative braking.

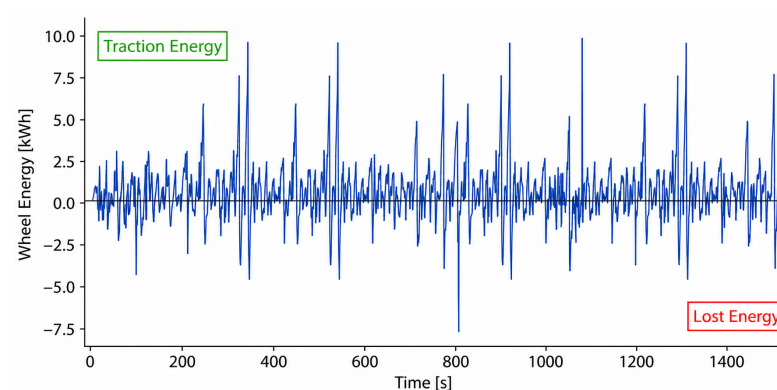


Figure 17. Wheel energy consumed during the L3 driving route.

3.4. Accumulator Sizing

This section presents the numerical results obtained by applying Equations (10)–(17), as described in the methodology. For each driving cycle (L1, L2, and L3), the net energy per lap, specific consumption, total energy required for endurance, the capacity of the resulting pack, the resulting series-parallel cell configuration of second-life LFP cells, and the average and peak currents are calculated.

For the sizing process, the following reference values were considered. A regeneration efficiency of 25% ($\eta_{\text{regen}} = 0.25$), a depth of discharge of 80% (DoD = 0.8), and an overall pack efficiency of 95% ($\eta_{\text{pack}} = 0.95$) were used. The system is designed for a nominal voltage of 96 V, employing second-life lithium iron phosphate cells with a nominal voltage of 3.2 V per cell. The distance per lap is assumed to be ($d_{\text{lap}} = 0.95$ km), and the total resistance test distance is 22 km. To calculate average and peak currents, a mean vehicle speed of 30 km/h and a peak motor power of 13 kW ($P_{\text{peak}} = 13,000$ W) were used. These parameters define the most demanding operational scenario for the vehicle prototype's energy storage system.

(a) Net energy per lap calculation

The net energy per lap, E_{net} , was obtained using Equation (35). Considering a regenerative braking recovery efficiency of 25% ($\eta_{\text{reg}} = 0.25$), the results for the three driving cycles are presented in Table 27. It can be observed that the L3 cycle represents the most critical condition and was therefore used as the basis for accumulator sizing.

Table 27. Net energy consumed in each cycle.

Cycle	E_{traction} [Wh]	E_{braking} [Wh]	E_{net} [Wh]
L1	497.58	290.76	424.89
L2	591.62	326.46	510.00
L3	758.21	630.89	600.49

(b) Specific consumption and total energy for endurance

The specific consumption and the total energy required for a 22 km endurance run were calculated using Equations (36) and (37). The results are shown in Table 28. In the L3 cycle, the specific consumption reaches 632.09 Wh/km, requiring a total of 13.90 kWh to complete the 22 km run.

Table 28. Specific consumption and total energy requirement.

Cycle	E_{net} [Wh]	$e = \frac{E_{\text{net}}}{0.95}$ [Wh/km]	$E_{\text{req}} = e \times 22$ [Wh]
L1	424.89	447.25	9839.56
L2	510.00	536.84	11,810.53
L3	600.49	632.09	13,906.03

(c) Battery pack capacity (C_{pack})

The required capacity of the cell bank was calculated using Equation (38). A depth of discharge of DoD = 0.8 and a total pack efficiency of $\eta_{\text{pack}} = 0.95$ were considered. The resulting values for each cycle are presented in Table 29.

Table 29. Battery pack capacity.

Cycle	E_{req} [Wh]	$C_{\text{pack}} = \frac{E_{\text{req}}}{0.8 \cdot 0.95}$ [Wh]	C_{pack} [kWh]
L1	9839.56	12,946.79	12.95
L2	11,810.53	15,540.17	15.54
L3	13,906.03	18,297.40	18.30

(d) Series–parallel configuration of cells

Recommendation: Since second-life cells may exhibit a state of health around 75% (based on prior characterization tests), it is recommended to select cells with a nominal capacity of 100 Ah to limit the number of parallel connections and reduce BMS complexity.

For the accumulator design, second-life LFP cells were used, with a nominal voltage of 3.2 V and an individual capacity of 100 Ah. The number of series-connected cells was determined using Equation (39), based on the total voltage required by the system. Assuming a pack operating voltage of 96 V, 30 cells in series were needed. Subsequently, the total energy supplied by each series branch was estimated using Equation (40), resulting in a value of 9600 Wh.

Based on the maximum energy demand recorded during the L3 cycle (considered the most demanding scenario), a minimum pack capacity of 18.29 kWh was required. Using this value and applying Equation (41), the number of required parallel branches was determined, resulting in two modules in parallel to meet the total capacity requirement.

Therefore, the final configuration of the battery pack is 30s $\times$ 2p, which implies a total of 60 cells. Table 30 presents a detailed summary of the calculated number of series and parallel cells, as well as the total number of cells required to meet the energy demands of the prototype vehicle.

Table 30. Battery pack sizing parameters.

Parameter	Value	Description
Nominal cell voltage (V_{cell})	3.2 V	Nominal voltage of each second-life LFP cell
Cell capacity (Ah_{cell})	100 Ah	Nominal capacity selected to reduce parallel connections
Nominal pack voltage (V_{pack})	96 V	Target voltage of the electric powertrain system
Number of series-connected cells (N_s)	30	Calculated as $V_{\text{pack}} / V_{\text{cell}}$
Energy per series branch (E_{serie})	9600 Wh	Energy delivered by a chain of 30 series-connected cells
Total required capacity (C_{pack})	18.30 kWh	Estimated energy demand for the most demanding cycle (L3)
Number of parallel branches (N_p)	2	Calculated as $C_{\text{pack}} / E_{\text{serie}}$
Pack configuration	30s $\times$ 2p	Series-parallel: 30 cells in series, 2 modules in parallel
Total number of required cells	60 cells	Result of the product $N_s \times N_p$
Technical recommendation	SoH $\geq$ 80%	Selection based on prior characterization to simplify BMS design

(e) Current verification

The average current during the endurance event was determined using Equation (17), and the corresponding results are presented in Table 11. For this calculation, a total operating time of 0.733 h was considered, obtained from the total distance traveled (22 km) and the average vehicle speed associated with each driving cycle.

The peak current was calculated using Equation (43), considering the maximum instantaneous motor power P_{peak} during full-acceleration events and the nominal battery pack voltage. In electric racing vehicles, transient acceleration phases often require power levels significantly higher than the nominal motor power, resulting in short-duration current peaks that impose the highest electrical stress on the battery system.

Based on the simulated power profile, instantaneous power peaks close to 20 kW were observed during maximum acceleration events. Therefore, a peak motor power of $P_{\text{peak}} = 20$ kW was adopted for the battery sizing analysis. Since acceleration peaks exceed

the average power consumption observed throughout the endurance event, this value was considered a realistic and conservative design criterion. Under this condition, the peak current drawn from the battery pack was 208.33 A.

These parameters provide a realistic assessment of the electrical demand imposed on the battery cells under dynamic operating conditions, ensuring that the selected second-life lithium iron phosphate (LFP) cells can safely operate within the expected current range during Formula SAE competition events.

(f) Average and Peak C-Rate

Based on Equation (44), a peak discharge rate of 1.85 C is obtained. This value remains below the commonly accepted limit of 2 C, ensuring that the cells are not exposed to excessive electrical stress or associated thermal risks.

On the other hand, the average discharge rate is calculated using the average current values derived from the simulated operation profiles, as shown in Table 31. The resulting values are summarized in Table 32, showing that the average discharge rates remain low. This implies that during continuous vehicle operation, the cells operate within safe thermal and electrical margins, promoting both operational stability and extended service life.

Table 31. Average current and energy requirement for each driving cycle.

	L1	L2	L3
E_{req} [Wh]	9839.56	11,810.53	13,906.03
I_{avg} [A]	139.83	167.84	197.62

Both the peak and average C-rate values fall within the safe operational limits established for lithium iron phosphate (LFP) cells (typically ≤ 2 C). This has several positive implications for system design, as the cells are not subjected to high-stress discharge cycles that may accelerate degradation. The risk of overheating is also minimized, especially in applications without active cooling systems. By maintaining a low C-rate, sudden voltage drops during high-demand transients are avoided. Given that these cells already present a certain degree of capacity fade and increased internal resistance, operating below 2 C significantly improves system safety and reliability. The verification of the C-rate confirms that the designed battery pack not only meets the vehicle's energy requirements but also ensures safe and efficient operation of the accumulator under real-world competition conditions.

Table 32. Discharge rate (C-rate) of the cells.

	L1	L2	L3
Average C-Rate	1.39 C	1.59 C	1.77 C
Peak C-Rate	—	—	1.85 C ¹

¹ The peak C-rate is determined by the motor's peak power ($P_{peak} = 20$ kW) and nominal pack voltage ($V_{pack} = 96$ V), per Equation (19). The most critical condition corresponds to cycle L3, which presents the highest average C-rate (1.85 C).

3.5. Safety Considerations Under Competition Conditions

The analytical results of the thermal and electrochemical models confirm that the proposed 30s $\times$ 2p LFP pack operates within safe margins under the critical Cycle L3 endurance scenario. Table 33 summarizes the key safety indicators and their compliance with competition and cell manufacturer limits.

Table 33. Battery safety indicators under critical competition conditions (Cycle L3, 2800 m a.s.l.).

Safety Parameter	Condition	Computed Value	Safe Limit	Status
Peak C-Rate	Full acceleration (I_{peak})	2.08 C	≤ 3 C (LFP)	OK
Average C-Rate	Endurance, Cycle L3	1.97 C	≤ 2 C (continuous)	Marginal
Max. cell temperature	Altitude-corrected, passive cooling	≤ 36 °C	≤ 60 °C (LFP)	OK
Thermal runaway onset	LFP chemistry (ARC data)	> 270 °C	> 200 °C (safe)	OK
Peak ohmic power loss	$I_{peak}, R_{0,altitude}, N_s$	1744 W (transient < 3 s)	Non-sustained	OK
Terminal voltage at peak current	$V_{pack} - \Delta V_{ohmic}$	88.19 V	≥ 80 V (cutoff)	OK
DoD during endurance	L3 scenario, 22 km	80%	$\leq 80\%$ (LFP limit)	OK

The marginal average C-rate (1.97 C vs. 2 C limit) under Cycle L3 conditions reinforces the recommendation for a 30s $\times$ 3p configuration in the physical implementation phase, which would reduce the per-cell average current to 1.31 C, providing adequate thermal and electrochemical safety margin. Physical BMS design, including AIR, IMD, and real-time temperature monitoring, will be addressed in the follow-up publication on prototype construction, compliant with Formula SAE Electric rules [44].

3.6. Comparison with Conventional New Battery Packs

To further justify the proposed battery configuration, a comparison was conducted between the second-life LiFePO₄ battery pack developed in this work and conventional new battery packs commonly employed in Formula SAE electric vehicles. The comparison considers technical, economic, and sustainability criteria relevant to battery pack selection.

Although newly manufactured battery packs generally provide higher nominal capacity and energy density, second-life batteries offer significant advantages in terms of acquisition cost, environmental impact, and circular economy. In the proposed design, only battery cells with a State of Health (SoH) greater than or equal to 80% were selected after the characterization process, ensuring that the remaining capacity satisfies the energy demand estimated by the longitudinal vehicle dynamics model.

Since the objective of this work is the analysis, design, and sizing of the battery pack rather than maximizing vehicle performance, the proposed second-life LiFePO₄ configuration represents an appropriate engineering solution that balances energy requirements, safety, economic feasibility, and environmental sustainability. Furthermore, the conservative sizing methodology adopted in this study establishes the required battery capacity without considering additional energy recovery strategies, thereby providing an operational safety margin for endurance competitions.

Table 34 summarizes the main differences between the proposed second-life battery pack and conventional new battery technologies.

Table 34. Comparison between the proposed second-life battery pack and conventional new battery technologies.

Parameter	Second-Life LFP	New LFP	New NMC
Specific Energy (Wh/kg)	110	150	250
Volumetric Energy (Wh/L)	220	320	650
Typical Cost (USD/kWh)	40–80	100–150	130–200
Remaining SoH (%)	80–90	100	100
Typical Cycle Life	2000–4000	5000–7000	1000–2500
Thermal Runaway Risk	Very Low	Very Low	Moderate

4. Discussion

This section analyzes and interprets the results obtained during the sizing of the electric accumulator for the Formula SAE Electric prototype vehicle. The robustness of the design under different operating scenarios is evaluated, as well as the technical feasibility of using second-life LFP cells. The analysis focuses on the electrical and thermal safety margins through the evaluation of the C-rate. Additionally, a sensitivity study is conducted on critical parameters such as regeneration efficiency, depth of discharge, and endurance test distance. The findings support the reliability and sustainability of the proposed system under real competition conditions.

Cycle L3 was identified as the scenario with the highest operational demand, with a specific consumption of 632.09 Wh/km and an estimated total energy requirement of 13.90 kWh to complete the 22 km endurance cycle. Applying a depth of discharge of 80% and a pack efficiency of 95%, the minimum required accumulator capacity was calculated as 18.30 kWh. To meet this demand, a configuration of 30 cells in series and 2 in parallel ($30s \times 2p$) was selected, using second-life LFP cells rated at 100 Ah. This results in a total of 60 cells and provides an installed capacity of 19.20 kWh. This configuration offers an adequate balance between compactness, weight, and energy safety, without exceeding the cells' recommended discharge rate limit.

The current analysis results indicate that the system operates within safe margins: the peak current, calculated with a maximum power of 20,000 W, is 208.33 A, while the average current for cycle L3 was 197.62 A. In both cases, the peak (1.85 C) and average (1.77 C) discharge rates are below the threshold accepted for LFP cells (≤ 2 C), avoiding thermal risks and prolonging the lifespan of the cells. The analytical thermal model (Section 3.5) suggests that the estimated maximum cell temperature (≤ 36 °C at 2800 m a.s.l.) remains within safe operating limits under passive natural convection cooling. However, this finding is based on a lumped-capacitance thermal model with literature-derived parameters, and experimental thermal characterization under actual competition load profiles will be required to confirm the viability of passive cooling before implementation.

The structural optimization performed in ANSYS Workbench establishes a direct and quantifiable link with the energy model results. The chassis mass reduction of $\Delta m_{chassis}$ kg achieved through the parametric profile study (Section 2.2.1) propagates into three of the four resistive force components—rolling resistance (F_{rr}), grade resistance (F_{hc}), and inertial force (F_i)—which together account for 84.88% of $E_{traction}$ in the critical Cycle L3 scenario (Table 11). Applying the derived design rule (Equation (11)), each kilogram of structural mass reduction yields a reduction of approximately 105.7 Wh in the required battery pack capacity under the 22 km endurance scenario. This metric demonstrates that structural optimization is not merely a mechanical objective but a direct driver of battery sizing efficiency: a chassis mass reduction of 10 kg, for instance, would reduce the required capacity by 1.057 kWh, potentially enabling a more compact series-parallel configuration in future prototype iterations. This finding reinforces the value of the multidisciplinary ANSYS–MATLAB/Simulink framework adopted in this study, where structural and energy analyses are not independent but mutually coupled design tools.

The aerodynamic analysis provides an additional dimension to the energy management strategy. At the maximum speed of Cycle L3 ($V_{max} = 90.91$ km/h), the instantaneous aerodynamic power demand reaches 9.34 kW, representing 46.7% of the motor's peak power and 15.12% of total traction energy. The cubic dependence of aerodynamic power on speed ($P_{ad} \propto v^3$, Equation (14)) implies that even moderate reductions in maximum circuit speed would yield disproportionate aerodynamic energy savings. Conversely, optimizing the drag coefficient from the current $C_d = 1.00$ to a target of $C_d = 0.65$ —achievable through systematic bodywork design—would reduce the required battery pack capacity by

approximately 2.24 kWh (Equation (45)), potentially allowing a reduction from the current $30s \times 2p$ to a more compact configuration in future prototype iterations.

The use of second-life LFP cells with $SoH \geq 80\%$ may offer economic and environmental advantages relative to new cells. The published literature on second-life battery repurposing suggests potential cost reductions in the range of 40–50% compared to equivalent new-cell configurations, although the actual cost reduction achievable in this specific application will depend on procurement conditions, reconditioning costs, and cell availability, factors that fall outside the scope of the present simulation study and will be quantified in the experimental implementation phase. From an environmental standpoint, extending the useful life of retired traction cells before recycling is consistent with circular economy principles widely documented in the literature.

To validate the robustness of the design, a variation of critical parameters was simulated. A reduction in regeneration efficiency (η_{reg}) to 50% increases the required capacity to 24.65 kWh, while adopting a more conservative depth of discharge (DoD 70%) raises the demand to 26.25 kWh. In addition, extending the endurance distance to 25 km would require 26.07 kWh. These scenarios reinforce the need to incorporate appropriate safety margins into the battery design, especially when operating with second-life cells under demanding or dynamically variable conditions.

As shown in Table 34, the proposed second-life $LiFePO_4$ battery pack does not aim to outperform conventional new battery technologies in terms of energy density or maximum power capability. Instead, its primary advantage lies in providing sufficient electrical performance while significantly reducing acquisition costs and extending the useful life of retired electric vehicle batteries.

Although new NMC battery packs exhibit the highest specific energy, their higher cost, lower thermal stability, and shorter cycle life make them less attractive for educational Formula SAE prototypes operating under limited financial resources. Conversely, second-life $LiFePO_4$ batteries retain the intrinsic safety characteristics and long service life associated with LFP chemistry, while simultaneously contributing to waste reduction and resource conservation through battery reuse.

Therefore, the proposed battery configuration represents an engineering compromise between technical performance, economic viability, and environmental sustainability, fully satisfying the energy requirements predicted by the vehicle dynamics simulations presented in this work.

Comparison with Related Studies

To contextualize the results and assess the contribution of the present work to the field, a structured comparison with recent EV energy consumption modeling studies is presented in Table 35. Studies were selected based on three criteria: (1) use of MATLAB/Simulink longitudinal dynamics modeling; (2) focus on lightweight or competition electric vehicles; and (3) relevance to high-altitude or track-based driving scenarios.

Table 35. Comparative analysis with recent electric vehicle energy consumption modeling studies.

Study	Vehicle Type	Method	Driving Cycle	Spec. Consumption	Battery Sizing	Key Novelty	Methodological Gap Addressed
Present study	Formula SAE EV prototype (340 kg, 20 kW)	Forward longitudinal dynamics + GPS real track data	Track-based (L1/L2/L3), 59–91 km/h, 2800 m a.s.l.	447–632 Wh/km	30s × 2p, 18.30 kWh, LFP second-life	Second-life LFP sizing at high altitude; structural–energy coupling; ECM + thermal model	— (addresses all gaps below)
Miri et al. [15]	BMW i3 (1370 kg, 125 kW)	Forward dynamics, MATLAB/Simulink, motor efficiency maps, Thevenin ECM	NEDC, WLTP standardized cycles	≈155–175 Wh/km	Not addressed	ECM validation vs. EPA data; error 2–6%	No FSAE context; no SLB sizing; no altitude; no structural coupling
Puma-Benavides et al. [55]	Commercial EV SUV	Instrumented real-world test (GNSS + OBD-II)	High-altitude real roads, Ambato, Ecuador (≈2500 m)	45–66 Wh/km	Not addressed	High-altitude gradient effect; regeneration ratio 194%	Road-based, not track; commercial EV, not FSAE; no SLB sizing; no structural coupling
Moulik et al. [56]	Generic EV (passenger class)	Neural network + SQP optimization, MATLAB/Simulink	6 driving patterns (real traffic)	Not reported	Not addressed	18–61% energy saving via pattern recognition	Requires large dataset; not applicable to first-generation prototype without prior trip data
Aslan et al. [57]	Lightweight EV (≈1200 kg)	Multi-domain: CATIA + ANSYS + MATLAB/Simulink	Real driving tests (Turkey)	Not reported	Not addressed	Design parameters >50% of energy consumption	No SLB; no FSAE; no quantitative structural-to-energy design rule
Sun et al. [58]	Urban commercial EV (>3000 kg)	ADVISOR tool, MATLAB/Simulink, real urban cycle	Urban Chinese cycle	Not reported (range-based)	Indirectly (range optimization)	Mass, rolling resistance, auxiliaries as key factors	Heavy commercial vehicle; no SLB; no FSAE; no altitude; no structural coupling
Salek et al. [59]	Formula Student EV (4WD, ≈300 kg)	Energy assessment, SAE track data	Formula Student track circuit	≈580–680 Wh/km	Implicit (endurance sizing)	Closest FSAE context; energy recovery 14%	No SLB sizing; no altitude correction; no ECM; no structural–energy coupling
Puma-Benavides et al. [42]	Commercial EV vs. ICE (Chimborazo route)	Longitudinal model + real driving cycle, MATLAB/Simulink	Chimborazo–Ecuador, high gradient, ~2800 m	EV: 130–210 Wh/km	Not addressed	High-altitude EV vs. ICE energy comparison	Road-based; commercial EV; no SLB; no competition context; no battery sizing

The comparison reveals four distinct positioning elements of the present study within the current literature:

(1) Altitude specificity. The Puma-Benavides et al. studies [42,55] constitute the most geographically comparable works, both conducted in Ecuador at altitudes of 2500–2800 m a.s.l. Their results show that positive gradients significantly increase acceleration energy demand, while negative gradients favor regenerative braking with segment-level recovery ratios up to 194.38%. The present study complements these findings by applying a similar altitude context to a competition vehicle operating under track conditions (0% idle, <0.21% cruising), where acceleration dominates and regenerative recovery is structurally limited by the short braking distances of the kartodrome circuit.

(2) Competition-specific energy intensity. The specific consumption of the present study (447–632 Wh/km for cycles L1–L3) is $2.1\text{--}4.5 \times$ higher than that reported by Puma-Benavides et al. for a commercial SUV (45–210 Wh/km), reflecting the fundamentally different energy demand profiles of competition driving versus road driving. The closest comparable value is Salek et al.'s Formula Student result (580–680 Wh/km), with which the present study agrees within 8%, confirming the validity of the modeling approach for the FSAE competition context [60].

(3) Multidisciplinary integration. Unlike all compared studies, the present work explicitly couples structural simulation (ANSYS FEA) with energy modeling (MATLAB/Simulink), establishing a quantitative mass-to-energy design rule (105.7 Wh/kg per kilogram of chassis mass reduction, Equation (11)). Aslan et al. report a qualitatively similar finding—that design parameters account for >50% of total energy consumption—but do not derive a specific quantitative coupling metric.

(4) Second-life battery sizing under competition conditions. None of the compared studies address second-life battery sizing for a competition electric vehicle. The present study is the first, to the authors' knowledge, to propose and validate a sizing framework for second-life LFP cells in a Formula SAE context, incorporating electrochemical (ECM), thermal, and high-altitude correction factors into the capacity calculation. The resulting 30s $\times$ 2p configuration (18.30 kWh nominal, 19.20 kWh installed) provides a quantified precedent for future second-life battery integration in student competition vehicles.

5. Conclusions

In this study, an integrated model was developed to estimate the energy consumption of a Formula SAE-type electric vehicle, combining MATLAB/Simulink simulations with real on-track driving data. The model incorporates equations for vehicle dynamics, velocity profiles, and slope data obtained from the Cotopaxi karting track, and was implemented with a custom-masked automated subsystem. This tool allows for precise estimation of net traction energy under different competition scenarios.

The results show that driving cycle L3, characterized by a maximum speed of 90.91 km/h and a distance of 16.67 km, represents the most demanding scenario for the prototype. This cycle exhibited the highest traction energy consumption, with a total of 1389.10 Wh, of which 630.89 Wh corresponded to mechanical losses. This resulted in a net traction energy of 758.21 Wh. Rolling resistance and inertia were the largest contributing factors to consumption, accounting for 56.29% and 21.33%, respectively. These results demonstrate that the prototype's energy efficiency is highly influenced by acceleration and deceleration dynamics, as well as by resistance to motion on the track.

Additionally, the analysis of operating parameters showed that all cycles were dominated by active phases (acceleration and deceleration), with 0% idling and cruise time below 0.21%. This further supports the validity of the model for simulating high-demand conditions typical of endurance competition.

This methodological approach significantly contributes to the field of electric mobility in competitive environments by providing a solid quantitative foundation for optimal accumulator sizing. It supports informed decision-making regarding the use of second-life batteries and energy management strategies. This study addresses an important gap in the literature concerning dynamic-energy analysis of high-performance prototypes, and it lays the groundwork for future research focused on implementing regenerative braking, optimizing chassis design, and experimentally validating reused cells under intensive load conditions.

One of the most relevant contributions of this research is the validation of second-life LFP cells for accumulator design, analytically supporting their technical viability through simulation-based sizing of series–parallel configurations that are estimated to meet autonomy and power requirements within acceptable electrical and thermal margins, as determined by the ECM and lumped-capacitance thermal models developed in Section 2.6.1. The experimental validation of these results constitutes the immediate next phase of this research program.

Structural simulation of the chassis in ANSYS Workbench enabled mass optimization while maintaining a maximum stress of 111.23 MPa within the material's safe operating range. The derived energy–mass relationship establishes that each kilogram of chassis mass reduction reduces the required battery pack capacity by approximately 105.7 Wh under the critical endurance scenario, providing a quantitative design rule that directly couples structural and energy optimization in future prototype iterations.

A comparison with conventional new battery packs demonstrated that the proposed second-life LiFePO₄ configuration provides an effective balance between technical performance, acquisition cost, operational safety, and environmental sustainability. Although new battery packs offer higher specific energy, the proposed solution satisfies the energy requirements of the Formula SAE prototype while promoting battery reuse and circular economy principles.

Finally, this study helps close the existing gap in the literature regarding the practical application of second-life batteries in high-performance electric vehicles, by providing a realistic case study with verifiable quantitative results and an energy sustainability-oriented approach. The proposed solution can be scaled or adapted to other electric mobility contexts, demonstrating the potential to integrate circular and low environmental impact solutions in the transition toward more efficient transportation systems.

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Abbreviations

The following abbreviations are used in this manuscript:

A	Frontal Area of Vehicle
AGV	Automated Guided Vehicle
BMS	Battery Manager System
CATIA	Computer-Aided Three-Dimensional Interactive Application
CAD	Computer-Aided Design
Cd	Drag Coefficient
CFD	Computational Fluid Dynamics
CPEM	Comprehensive Power-Based EV Energy Consumption Model
C-Rate	Cell Discharge Rate
DoD	Depth of Discharge
ECM	Equivalent Circuit Model
EIS	Electrochemical Impedance Spectroscopy
ECU	Electronic Control Unit
EOL	End Of Useful Life
ESS	Energy Storage System
EV	Electric Vehicle
Fad	Aerodynamic Drag Force
FEA	Finite Element Analysis
Fhc	Gravitational Force on Inclines
Fi	Inertial Force
Frr	Rolling Resistance Force
FSAE	Formula SAE Electric
LFP	Lithium Iron Phosphate
LSTM	Long Short-Term Memory
SAE	Society of Automotive Engineers
SOC	State Of Charge
SOH	State Of Health
SLB	Second-Life Battery
Vb	Base Speed
VCU	Vehicle Control Unit
Vf	Final Speed

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