

Impact of Driving-Cycle Characteristics on Electric-Vehicle Battery Performance: A Bayesian-Optimization Framework

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ABSTRACT

The energy consumption of electric vehicles (EVs) is significantly influenced by driving behavior, yet battery packs are often sized against uniform standard test cycles. This work presents a dual contribution: an empirical analysis of battery sizing sensitivity across transient driving conditions and a critical diagnostic evaluation of composite objective formulations in multi-parameter battery optimization. We couple a MATLAB/Simulink electro-thermal EV powertrain model with a Bayesian optimizer using a Gaussian-process surrogate to size cell capacity (C_{cell}), series cell count (N_s), and parallel string count (N_p) across four standard MATLAB-sourced drive cycles (Urban, Highway, Mixed, and Aggressive) matched for total distance (16.3–17.8 km). Empirically, specific energy consumption increased from 89.60 Wh/km (Urban) to 166.97 Wh/km (Aggressive), an 86.3% rise driven by transient peak power demands rather than mean speed. Methodologically, we demonstrate that standard composite sizing objectives suffer from structural degeneracy: while total pack energy ($N_s N_p C_{cell}$) is uniquely identified, the individual series–parallel topology (N_s vs. N_p) remains underdetermined when SOC, thermal, and current penalty constraints remain inactive at convergence. Identifying and isolating this objective non-uniqueness provides a methodological framework for EV powertrain optimization, preventing unsupported claims of global optimality in under-constrained battery-pack designs.

Keywords: Bayesian optimization, battery pack sizing, regenerative braking, electric vehicles, drive cycles, energy consumption, Gaussian process, MATLAB

1. INTRODUCTION

The worldwide automobile industry is swiftly shifting toward electric vehicles (EVs) as countries aim for decarbonization goals and improved urban air quality. The International Energy Agency indicates that global electric vehicle sales have persistently increased, with EVs currently constituting a significant and expanding portion of new vehicle registrations [1]. Although this transition offers significant ecological and health advantages, widespread acceptance continues to encounter two enduring obstacles: "range

anxiety," the apprehension that the battery may not last for a full day's journey ; and worries regarding the long-term deterioration of the battery. Enhancing the practical energy efficiency of electric vehicles is crucial for increasing range, extending battery lifespan, and reducing overall ownership costs.

Energy consumption in electric vehicles is significantly more affected by driving circumstances compared to traditional automobiles. In contrast to real-world urban driving, which is dominated by frequent stops, traffic jams, and signals, steady highway cruising results in predictable, efficient usage. Every transient necessitates substantial peak power to surmount vehicle inertia; the consequent elevated currents amplify ohmic losses in the battery, inverter, and motor windings, transforming valuable energy into irretrievable waste heat [2], [3]. Despite the fact that regenerative braking recaptures a portion of the kinetic energy during deceleration, the round-trip efficiency of an acceleration-regeneration cycle is significantly lower than 100%, resulting in a quantifiable net energy penalty.

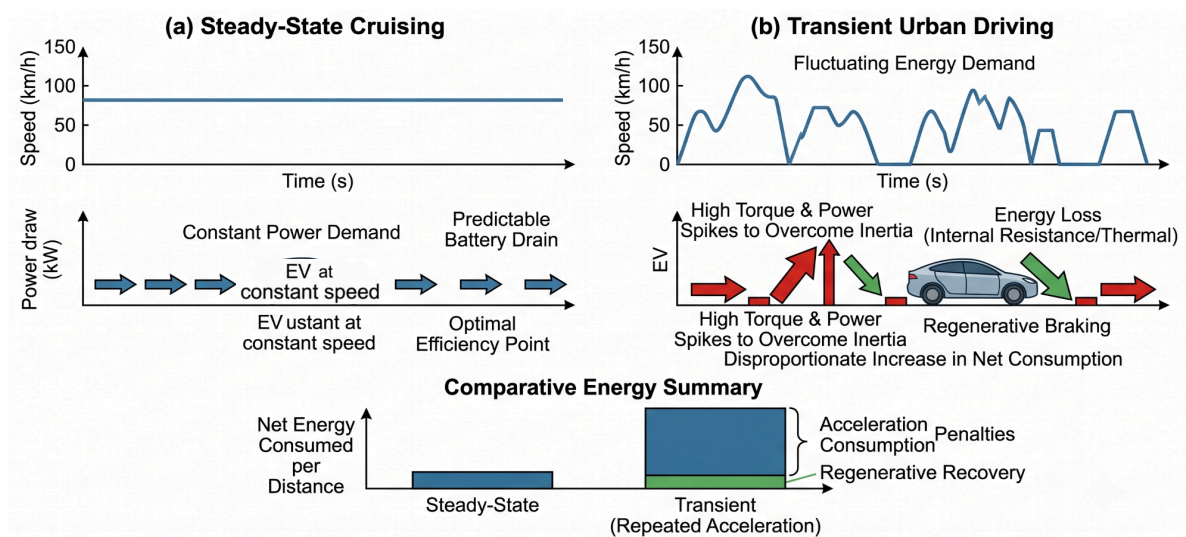


Figure 1. The impact of successive acceleration cycles on electric vehicle energy usage. Constant-speed cruising (left) utilizes about uniform power, but fluctuating urban driving (right) requires intermittent high-power surges; insufficient regenerative recovery results in a net energy deficit.

A significant amount of research has investigated regenerative braking and driving behavior. Huda et al. demonstrated through experimentation that activating regenerative braking on a modified electric vehicle decreased average energy consumption by approximately 6.16% in varied settings [3]. Lee et al. found through on-road evaluations that higher regenerative braking levels improved energy recovery and reduced overall consumption, but the advantage varied with traffic conditions and speed [2]. Wang et al. utilized actual GPS data from Beijing to indicate that congested urban patterns characterized by frequent acceleration expended significantly more energy than anticipated by standardized cycles [4]. Szumska further highlighted that regular, moderate braking might enhance recovery, but forceful acceleration still results in excessive losses when the powertrain operates outside its optimal range during high-power fluctuations. Research on Indian circumstances corroborates this: specific driving patterns like the Delhi

Driving Cycle and several Indian cycles regularly demonstrate that congested, fluctuating urban traffic results in greater per-kilometer fuel consumption compared to foreign cycles like Worldwide Harmonised Light Vehicles Test Procedure (WLTP) or New European Driving Cycle (NEDC).

Notwithstanding these contributions, deficiencies persist. The majority of studies either compare general standardized cycles or assess total regenerative efficiency, neglecting to isolate acceleration frequency and intensity as controllable factors while keeping the distance constant.

This study addresses that gap by coupling a physics-based EV powertrain simulation to a Bayesian optimizer [9]–[11]. Bayesian optimization is well suited to expensive black-box simulations because it builds a Gaussian-process surrogate of the objective and uses an acquisition function to choose informative evaluations [12]–[14]. We optimize the cell capacity and the series/parallel configuration independently for four drive cycles that share nearly identical distances but differ in transient content, and we compare the resulting designs on energy, range, current, thermal behavior, and state of charge. The specific objectives are:

1. to optimize the battery-pack parameters (C_{cell} , N_s , N_p) for each drive cycle;
2. to evaluate specific energy consumption, final state of charge (SOC), peak pack current, and temperature for each optimized design;
3. to quantify how acceleration frequency and intensity, at matched total distance, change consumption and peak current; and
4. to critically examine the optimization objective itself, showing why an energy- and mass-dominated objective leaves the series–parallel split weakly identified, and what would be required to restore a physically meaningful interior optimum.

2. METHODS

A simulation-based optimization framework was created using Simscape Driveline and MATLAB/Simulink [15]. While continuously recording pack voltage, current, state of charge (SOC), energy, temperature, and vehicle speed, a forward-facing electric vehicle (EV) powertrain model which includes a longitudinal driver, drive-cycle source, battery pack, electric motor and inverter, transmission, vehicle body, wheels, and a lumped battery thermal model, simulates realistic operation. The battery design variables are updated and the closed-loop simulation is re-evaluated by an outer Bayesian-optimization loop until the evaluation budget is depleted.

2.1. Overview of the Model and Powertrain Architecture

The battery pack is modeled as a lithium-ion pack of cells in series and parallel. The series count N_s determines the pack's voltage, while the parallel count N_p determines its capacity and current-handling capability. A longitudinal driver model monitors the commanded speed of the active drive cycle, while the pack powers a motor/inverter via a single-ratio transmission. The cell temperature is estimated using a

lumped thermal model based on convective cooling and ohmic heating. Signals are recorded at each time step and transmitted to an energy/range calculator, which then provides the optimizer with the scalar objective. The longitudinal dynamics of the pack adhere to conventional vehicle-propulsion modeling [18], [19], while the dynamic behavior follows the widely used controlled-voltage-source lithium-ion representation [16], [17]. The architecture and the closed-loop coupling to the optimizer are illustrated in Figure 2.

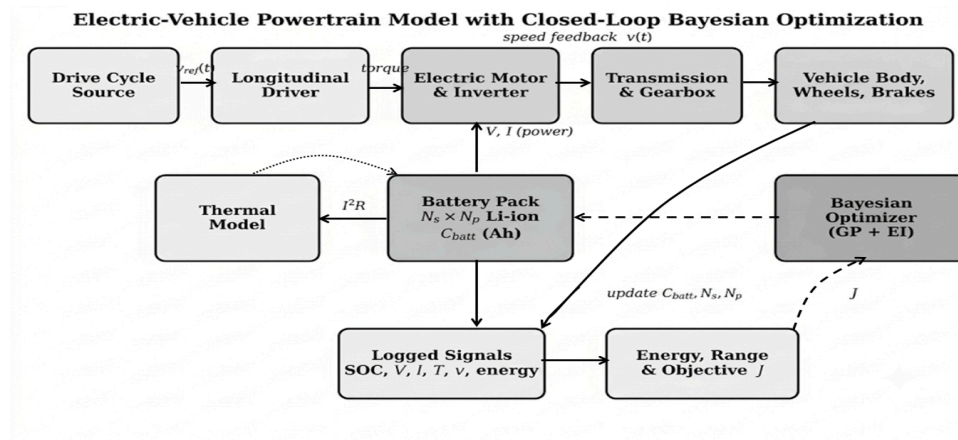


Figure 2. Electric-vehicle powertrain architecture implemented in MATLAB/Simulink. Solid arrows show physical and signal flow; the Bayesian optimizer (dashed loop) updates C_{cell} , N_s , and N_p and re-evaluates the simulation.

The corresponding Simulink implementation is shown in Figure 3. The drive-cycle source feeds the longitudinal driver block, whose normalized acceleration and deceleration commands drive the mapped motor and inverter; the Datasheet Battery block supplies pack voltage and current, and all logged signals are collected on a single bus for the objective evaluation.

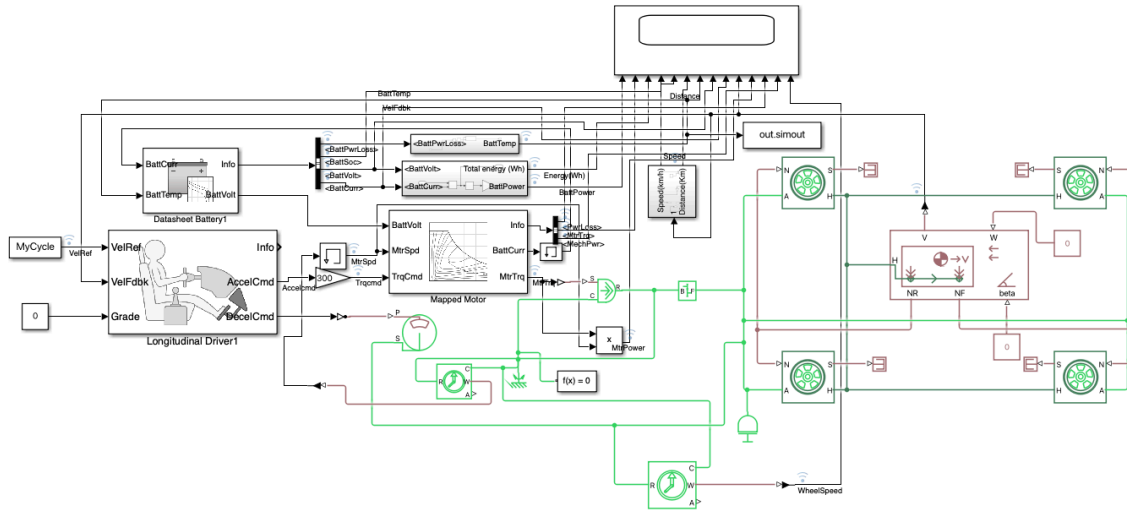


Figure 3. Simulink implementation of the forward-facing electric-vehicle powertrain and electro-thermal battery model.

The model routes battery feedback metrics: instantaneous pack voltage, current, temperature, SOC, cumulative energy consumed, vehicle speed, and distance travelled—into a centralized signal bus for evaluation by the Bayesian-optimization loop.

2.2. Driver, Motor, and Vehicle Dynamics

Closed-loop tracking of the target velocity profile is governed by a proportional–integral (PI) longitudinal driver block. Comparing the reference velocity v_{ref} against the vehicle speed feedback v_{fdbk} , the driver outputs normalized acceleration and deceleration commands:

$$AccelCmd(t) = \max(0, K_p e(t) + K_i \int e(t) dt), DecelCmd(t) = \max(0, -K_p e(t) - K_i \int e(t) dt), \quad (1)$$

where $e(t) = v_{ref}(t) - v_{fdbk}(t)$. Road grade θ is set to zero across all drive-cycle evaluations, isolating aerodynamic, rolling-resistance, and acceleration energy demands.

The powertrain uses a Mapped Motor block operating in torque-control mode. The acceleration command is scaled to a target motor torque demand bounded by the motor’s maximum torque–speed envelope:

$$T_{cmd} = AccelCmd \cdot T_{max}(\omega_m). \quad (2)$$

The motor converts mechanical power demand $P_{mech} = T_m \omega_m$ into electrical power demand P_{elec} using efficiency lookup tables derived from motor–inverter efficiency maps $\eta(T_m, \omega_m)$:

$$P_{elec} = \begin{cases} \frac{T_m \omega_m}{\eta(T_m, \omega_m)}, & \text{traction mode } (T_m \geq 0), \\ T_m \omega_m \eta_{regen}(T_m, \omega_m), & \text{regenerative braking } (T_m < 0). \end{cases} \quad (3)$$

The mechanical drivetrain transfers motor torque to the four wheels through a gear reduction ratio i_g and a differential. The vehicle body block models longitudinal dynamics including aerodynamic drag, rolling resistance, and inertial acceleration:

$$F_{traction} = \frac{T_m i_g \eta_{driveline}}{R_w}, \quad m_{total} \frac{dv}{dt} = F_{traction} - F_{aero} - F_{roll}, \quad (4)$$

with the resistance forces defined as

$$F_{aero} = \frac{1}{2} \rho_a C_d A_f v^2, \quad F_{roll} = C_{rr} m_{total} g \cos \theta. \quad (5)$$

The total vehicle mass is $m_{total} = m_{chassis} + m_{battery}$, so the optimized battery mass couples directly back into vehicle dynamics and energy consumption.

2.3. Coupled Electro-Thermal Battery Model

The Datasheet Battery block simulates the electrical and thermal response of a lithium-ion pack configured with N_s cells in series and N_p branches in parallel.

Electrical dynamics. Each cell is represented by an equivalent-circuit model with open-circuit voltage $V_{oc}(SOC)$ and internal resistance $R_{int}(SOC, T_{batt})$:

$$V_{pack} = N_s [V_{oc}(SOC) - I_{cell} R_{int}(SOC, T_{batt})], \quad I_{pack} = N_p I_{cell} = \frac{P_{elec}}{V_{pack}}. \quad (6)$$

State of charge is tracked by Coulomb counting:

$$SOC(t) = SOC_0 - \frac{1}{C_{cell} N_p} \int_0^t I_{pack}(\tau) d\tau. \quad (7)$$

Thermal dynamics. Heat generation within the pack accounts for internal-resistance power loss,

$$Q_{gen} = I_{pack}^2 R_{pack} = N_s N_p I_{cell}^2 R_{int}(SOC, T_{batt}), \quad (8)$$

and a lumped-parameter thermal balance determines the temperature rise:

$$m_{battery} C_p \frac{dT_{batt}}{dt} = Q_{gen} - hA_{cooling}(T_{batt} - T_{amb}), \quad (9)$$

where C_p is the specific heat capacity, h the convective cooling coefficient, $A_{cooling}$ the cooling surface area, and $T_{amb} = 25^\circ \text{C}$ the ambient temperature.

2.4. Drive-Cycle Definitions

Four representative cycles span a range of real-world conditions. The drive cycles are standard MATLAB drive-cycle profiles selected for this study and are distance-matched based on their available profiles, rather than being custom-synthesized to achieve a predetermined distance. All four cover closely matched total distance (16.3–17.8 km), so differences in specific energy consumption reflect *how* the vehicle is driven rather than *how far*. The cycles differ chiefly in duration, peak velocity, and acceleration content. Their velocity profiles are shown in Figure 4 and their characteristics summarized in Table 1. This distance-matched selection enables the study to isolate the effect of transient driving behaviour from mean vehicle speed. Specifically, the results examine whether specific energy consumption (Wh/km) is more strongly associated with transient acceleration intensity than with average vehicle speed. The drive-cycle analysis is incorporated into a coupled Simulink–Bayesian optimization framework that accounts for thermal limits, battery-cell mass penalties, and speed-tracking constraints when evaluating battery-pack configurations.

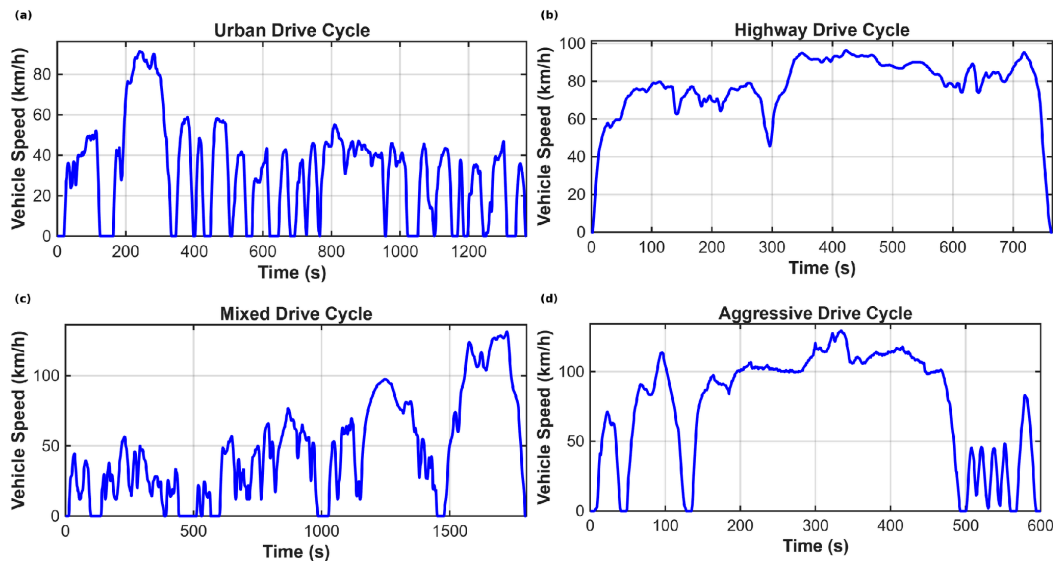


Figure 4. Reference velocity profiles of the four evaluated drive cycles: (a) Urban (1370 s), (b) Highway (765 s), (c) Mixed (1800 s), and (d) Aggressive (600 s).

Table 1. Characteristics of the four drive cycles. Distance and average speed are derived from the logged simulation output of the converged designs.

Drive Cycle	Primary Character	Duration(s)	Distance (km)	Avg. speed(km/h)
Urban	Dense stop-and-go, low speed	1370	16.34	42.9
Highway	Near-constant cruise	765	17.77	83.6
Mixed	City plus highway segments	1800	17.34	34.7
Aggressive	Rapid acceleration and hard braking	600	16.51	99.1

The four drive cycles evaluated in this study correspond directly to standard reference profiles built into the MATLAB/Simulink Drive Cycle Source block (Powertrain Blockset): FTP-75 (Urban), HWFET (Highway), WLTP Class 3 (Mixed), and US06 (Aggressive).

Urban cycle (1370 s). Low average velocity with repeated acceleration–deceleration micro-cycles and long idle periods. Regenerative braking recovery is high, while aerodynamic drag remains modest.

Highway cycle (765 s). Sustained velocity in the 70–95 km/h band with minimal stop–start transients. Power demand is dominated by continuous aerodynamic resistance, $F_{drag} \propto v^2$.

Mixed cycle (1800 s). Combines low-speed urban congestion (0–1000 s) with a high-velocity segment (1500–1800 s) exceeding 120 km/h, testing system endurance across a broad power band. This cycle has the *lowest* average speed of the four yet consumes more per kilometre than the Urban cycle, isolating the effect of transient content from mean velocity.

Aggressive cycle (600 s). Sharp velocity spikes above 125 km/h with acceleration transients exceeding 2.5 m/s^2 . High discharge-current surges induce significant resistive I^2R heating. This cycle combines both the highest average speed and the highest transient content, so its consumption penalty relative to Urban reflects both effects.

2.5. Vehicle and Simulation Parameters

A generic mid-size EV was modelled. Total vehicle mass is the sum of a fixed glider mass and the battery mass returned by the sizing model, so heavier packs feed back into the energy calculation. Key parameters are listed in Table 2. All remaining vehicle-body, driveline, and driver parameters – aerodynamic drag coefficient and frontal area, rolling-resistance coefficient, wheel radius, gear ratio, driver PI gains, and cell internal resistance – were retained at the default values of the corresponding Simscape Driveline and Datasheet Battery blocks.

Table 2. Vehicle, cell, and simulation parameters.

Parameter	Symbol	Value
Base (glider) mass	$m_{chassis}$	1200 kg
Nominal cell voltage	V_{cell}	3.7 V
Cell specific energy	η_{spec}	180 Wh/kg
Pack packaging factor	PF	1.20
Initial state of charge	SOC_0	100%
Ambient temperature	T_{amb}	25 °C (298.15 K)
Auxiliary load	P_{aux}	350 W
Road grade	θ	0
Maximum objective evaluations	—	60 per cycle

2.6. Energy, Range, and Battery-Mass Calculations

After each simulation the total energy E (Wh) and distance d (km) give the specific consumption E/d (Wh/km). Nominal pack energy and estimated range follow as

$$E_{pack} = N_s V_{cell} C_{cell} N_p, R = \frac{E_{pack}}{E/d}. \quad (10)$$

Pack mass is estimated from pack energy, the cell specific energy η_{spec} , and a packaging factor PF accounting for module hardware, enclosure, and thermal-management mass:

The cell specific energy ($\eta_{spec}=180$ Wh/kg) reflects standard commercial lithium-ion phosphate (LiFePO4) pouch/cylindrical cell technology. A pack packaging factor of $PF=1.20$ is applied to account for the overhead mass of structural enclosures, busbars, thermal-management cold plates, and the Battery Management System (BMS) wiring harness, aligned with established EV pack design literature [22].

$$m_{battery} = \frac{V_{cell} N_s C_{cell} N_p}{\eta_{spec}} \cdot PF = \frac{E_{pack}}{\eta_{spec}} \cdot PF, \quad (11)$$

which for $\eta_{spec} = 180$ Wh/kg and $PF = 1.20$ corresponds to an effective pack-level gravimetric energy density of 150 Wh/kg. The total simulated mass is $m_{total} = m_{chassis} + m_{battery}$.

2.7. Design Variables and Search Bounds

The optimizer selects three design parameters: the maximum single-cell charge capacity C_{cell} , the number of cells in series N_s , and the number of parallel branches N_p . The decision vector is

$$x = [C_{cell} \ N_s \ N_p], \quad (12)$$

with box bounds

$$C_{cell} \in [25.0, 60.0] \text{ Ah} \quad (\text{continuous}), \ N_s \in [90, 110] \quad (\text{integer}), \ N_p \in [3, 8] \quad (\text{integer}). \quad (13)$$

The total pack nominal capacity follows as $PackCapacity = C_{cell} N_p$.

2.8. Objective Function and Constraints

The multi-attribute objective $J(x)$ balances energy economy, pack weight, velocity-tracking precision, and thermal performance while enforcing operational safety constraints. Four metrics are normalized onto the unit interval to prevent scale dominance among conflicting physical units:

$$\begin{aligned} S_E &= \min\left(\frac{E_{per-km}}{200}, 1.0\right), \ S_M = \min\left(\frac{m_{battery}}{500}, 1.0\right), \\ S_S &= \min\left(\frac{SpeedRMSE}{5.0}, 1.0\right), \ S_T = \min\left(\max\left(\frac{T_{max}-T_{amb}}{T_{limit}-T_{amb}}, 0\right), 1.0\right) \end{aligned} \quad (14)$$

where the velocity-tracking error is

$$SpeedRMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (v_{ref,i} - v_{fdbk,i})^2}, \quad (15)$$

with $T_{amb} = 298.15 \text{ K}$ (25 °C) and $T_{limit} = 318.15 \text{ K}$ (45 °C). The unconstrained weighted sum is

$$J_{base}(x) = w_E S_E + w_M S_M + w_S S_S + w_T S_T, \quad (16)$$

with weights chosen to prioritize range and efficiency while retaining thermal safety:

$$w_E = 0.45, \quad w_M = 0.20, \quad w_S = 0.15, \quad w_T = 0.20, \quad \sum w = 1.0. \quad (17)$$

The weighting scheme reflects the relative priorities of the optimization objectives. Energy efficiency is assigned the largest weight ($w_E = 0.45$) because energy consumption directly influences driving range and overall powertrain efficiency. Battery mass and thermal performance are each assigned a weight of 0.20. The mass weighting discourages excessive battery sizing, since increased pack mass increases the

vehicle's energy and traction requirements, while the thermal weighting promotes operation within the specified temperature limit and discourages excessive thermal loading. Velocity-tracking accuracy is assigned the lowest weight ($w_s = 0.15$), as accurate reproduction of the target drive cycle is necessary for a valid simulation but is also governed by the physical constraints of the vehicle and powertrain model. Thus, the weighting prioritizes energy efficiency while maintaining balanced consideration of battery mass, thermal performance, and dynamic tracking accuracy.

Quadratic exterior penalty functions enforce state-of-charge, thermal, range, and current thresholds:

$$P(x) = P_{SOC} + P_{Temp} + P_{Range} + P_{Curr}, \quad (18)$$

$$P_{SOC} = 1000 \left[\max\left(0, SOC_{min} - SOC\right) \right]^2, \quad SOC_{min} = 0.20, \quad P_{Range} = 100 \left[\max\left(0, \frac{R_{min} - R}{R_{min}}\right) \right]^2, \\ R_{min} = 300.0 \text{ km}, \quad P_{Curr} = 100 \left[\max\left(0, \frac{I_{max} - I_{allow}}{I_{allow}}\right) \right]^2, \quad I_{allow} = 300.0 \text{ A}. \quad (19)$$

The final value returned to the optimizer is

$$J(x) = J_{base}(x) + P(x). \quad (20)$$

If a simulation fails or encounters an integration error, an execution penalty $J = 10^9$ is returned.

2.9. Optimization Algorithm and Software Implementation

Because each evaluation of $J(x)$ requires a full closed-loop Simulink simulation, the iterative Bayesian-optimization algorithm bayesopt was employed [20]. A Gaussian-process regression model is constructed as a surrogate for the unobserved objective surface $J(x)$, and the expected-improvement-plus acquisition function navigates the trade-off between exploring unvisited design regions and exploiting known local minima [10]–[12], [21]. Execution parameters were: 60 maximum objective evaluations per cycle; deterministic objective flag set true (IsObjectiveDeterministic = true); fixed random seed (rng(1)); and parallel evaluation enabled across available compute threads. Note that with parallel evaluation enabled, a fixed seed guarantees repeatability of the initial design but not bit-identical reproduction of the full run, because the order in which workers return evaluations is not deterministic.

The pipeline comprises five MATLAB modules: MainOptimization.m (master script: loads cycles, launches independent runs, stores results, and generates tables and plots); initializeEVModel.m (loads the drive cycle and assigns parameters); objectiveFcn.m (runs the Simulink model, computes metrics, applies penalties, and returns J); estimateBatteryMass.m (pack-mass estimate per Equation (11)); and evaluateBestBattery.m (final high-resolution evaluation of the converged design).

3. RESULTS

Bayesian optimization was performed independently for each of the four drive cycles using three independent random seeds, with 60 function evaluations per seed, resulting in 180 evaluations per drive cycle.

3.1. Optimized Battery Configurations

Table 3 lists the converged configurations and the derived pack quantities, and Table 4 the corresponding performance metrics. Pack voltage is $V_{pack} = N_s V_{cell}$ and pack energy is $E_{pack} = N_s N_p C_{cell} V_{cell}$.

Table 3. Converged battery configuration for each drive cycle.

Drive cycle	C_{cell} (Ah)	Pack cap. (Ah)	N_s	N_p	Pack voltage (V)	Pack energy (kWh)
Urban	25.25	75.75	98	3	362.60	27.47
Highway	25.08	100.32	110	4	407.00	40.83
Mixed	32.03	96.10	90	3	333.00	32.00
Aggressive	25.01	125.06	110	5	407.00	50.90

Table 4. Performance metrics of the converged designs, as logged by the Simulink evaluations.

Drive cycle	Energy (Wh)	Wh/km	I_{max} (A)	Final SoC (%)	ΔT (°C)	Mass (kg)	Range (km)
Urban	1464.19	89.60	142.22	95.21	2.65×10^{-4}	183.12	306.58
Highway	2317.43	130.39	112.55	94.94	2.11×10^{-4}	272.21	313.14
Mixed	1850.67	106.74	153.77	94.78	5.25×10^{-4}	213.35	299.81
Aggressive	2757.08	166.97	257.22	95.12	3.64×10^{-4}	339.32	304.83

Table 5. Bayesian Optimization Results for Objective Function Performance Across Drive Cycles, as logged by the Simulink evaluations.

Drive cycle	SpeedRMSE (m/s)	Objective	Obj_Mean	Obj_Std
Urban	4.59	0.41	0.40	4.69×10^{-05}
Highway	2.75	0.48	0.43	1.76×10^{-05}
Mixed	3.70	0.43	0.41	6.49×10^{-05}
Aggressive	6.73	0.66	0.57	1.68×10^{-05}

Cell nominal capacity. The optimizer gravitated toward the lower bound ($C_{cell} \approx 25.0\text{--}25.25$ Ah) for the Urban, Highway, and Aggressive cycles. Smaller individual cells provide finer granularity for scaling the parallel count N_p without incurring excess pack mass. The Mixed cycle instead selected 32.03 Ah paired with $N_p = 3$ and $N_s = 90$: with both integer counts at their lower bounds, a larger cell was the only remaining route to the required pack energy.

Series configuration. The Highway and Aggressive cycles reached the upper bound $N_s = 110$ ($V_{pack} = 407.0$ V), while the lower-speed Urban and Mixed profiles used $N_s = 98$ (362.6 V) and $N_s = 90$ (333.0 V) respectively. Higher terminal voltage reduces pack current for a given power demand and therefore suppresses I^2R conductive loss.

Parallel configuration and pack energy. Parallel sizing scaled with duty-cycle intensity: $N_p = 3$ for Urban and Mixed, $N_p = 4$ for Highway, and $N_p = 5$ for Aggressive. Total pack energy grew from 27.47 kWh (Urban) to 50.90 kWh (Aggressive), ensuring the 300 km minimum-range constraint was satisfied despite the higher consumption rates.

3.2. Energy Consumption and Transient Severity

Figure 5 shows the total net energy drawn during each cycle and the corresponding specific consumption. Total energy scales with both cycle duration and dynamic intensity: the Urban cycle registered the lowest cumulative demand at 1464.19 Wh, reflecting low average speed and substantial regenerative recovery, while the Aggressive cycle recorded the highest at 2757.08 Wh, an 88.3% increase over Urban.

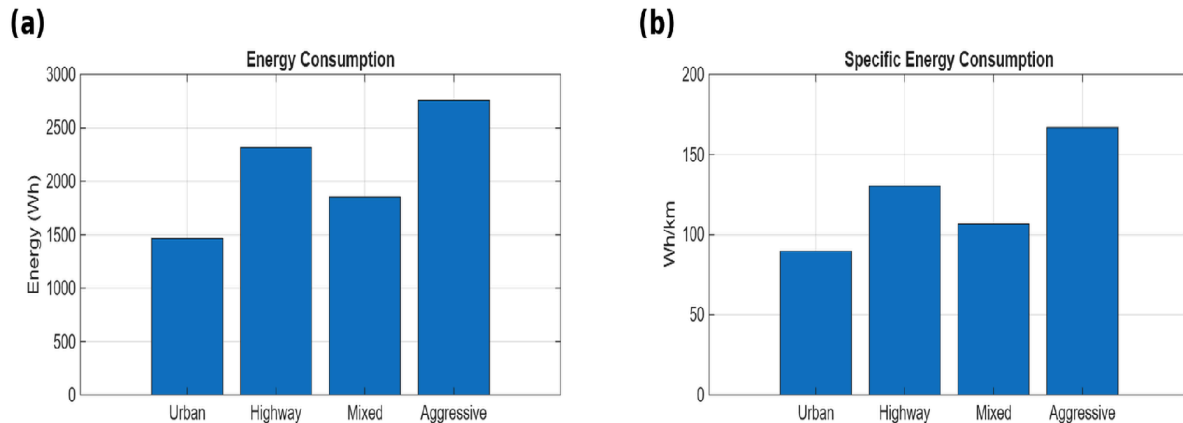


Figure 5. Energy performance of the optimized configurations: (a) net energy drawn per cycle; (b) specific energy consumption in Wh/km.

Normalizing by distance isolates powertrain efficiency. Urban driving was the most efficient at 89.60 Wh/km, benefiting from low average velocity where aerodynamic resistance remains minimal. The Mixed profile consumed 106.74 Wh/km, the Highway profile 130.39 Wh/km under sustained high-velocity air resistance, and the Aggressive profile 166.97 Wh/km, an 86.3% increase relative to Urban, caused by frequent rapid discharge transients and heightened internal resistive losses.

Two comparisons within this set separate the effect of transient content from that of mean velocity. First, the Mixed cycle has the lowest average speed of the four (34.7 km/h, below the Urban cycle's 42.9 km/h) yet consumes 19.1% more energy per kilometre, because its high-velocity closing segment exceeds 120 km/h. Second, the Highway cycle sustains 83.6 km/h with almost no transients and consumes 130.39 Wh/km, whereas the Aggressive cycle at 99.1 km/h with frequent high-amplitude transients consumes 166.97 Wh/km, a 28.1% increase for an 18.5% increase in average speed. Together these indicate that peak power demand, not mean velocity, is the stronger predictor of specific consumption within this cycle set.

3.3. Current, State of Charge, and Thermal Behaviour

Figure 6 summarizes the electrical and thermal response of the converged designs.

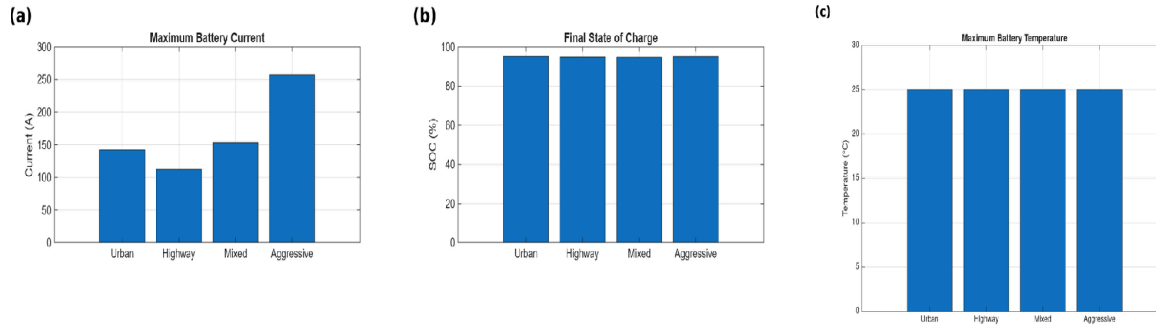


Figure 6. Electrical and thermal response of the optimized configurations: (a) peak pack current; (b) final state of charge; (c) peak cell temperature.

Peak discharge current was lowest for the Highway configuration at 112.55 A, consistent with its maximum series count ($N_s = 110$, $V_{pack} = 407.0$ V) reducing current for a given power delivery. The Urban and Mixed profiles showed moderate peaks of 142.22 A and 153.77 A driven by transient acceleration demands. The Aggressive profile induced the highest current stress at 257.22 A, remaining below the 300 A soft-constraint boundary so that $P_{Curr} = 0$ at every converged design. Expressed per cell, these correspond to 1.88C (Urban), 1.12C (Highway), 1.60C (Mixed), and 2.06C (Aggressive).

Final SOC fell in a narrow band of 94.78% to 95.21% across all four architectures. This reflects the fact that a single 16–18 km cycle depletes only about 5% of a 27–51 kWh pack; the state-of-charge penalty was therefore structurally unreachable and $P_{SOC} = 0$ throughout. Peak cell temperature likewise remained at the 25.0 °C ambient value to within 5.25×10^{-4} °C, giving $S_T \approx 10^{-5}$ and $P_{Temp} = 0$ for every candidate design.

3.4. Range and Composite Objective

Figure 7 shows the selected cell capacity, resulting pack mass, and estimated range. Pack mass scaled linearly with pack energy by construction, from 183.12 kg for the Urban design (total vehicle mass 1383.12 kg) through 213.35 kg (Mixed) and 272.21 kg (Highway) to 339.32 kg for the Aggressive design, an 85.3% increase over Urban. All four configurations converged just above the 300 km target, spanning 299.81 to 313.14 km, confirming that the optimizer sized pack energy to match each cycle’s consumption

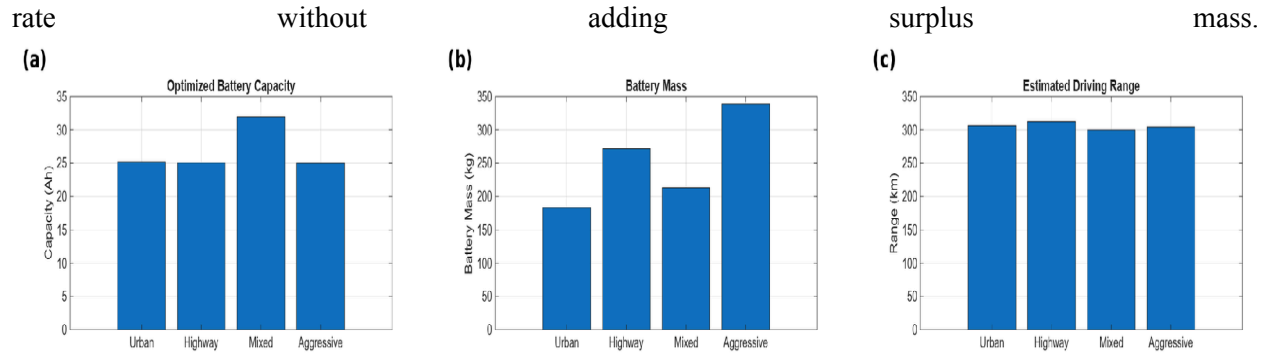


Figure 7. Optimized pack architecture and range: (a) selected single-cell nominal capacity; (b) pack mass; (c) estimated driving range.

The composite objective, shown in Figure 8, ordered the cycles as

$$J_{Urban} = 0.4132 < J_{Mixed} = 0.4376 < J_{Highway} = 0.4878 < J_{Aggressive} = 0.6614. \quad (21)$$

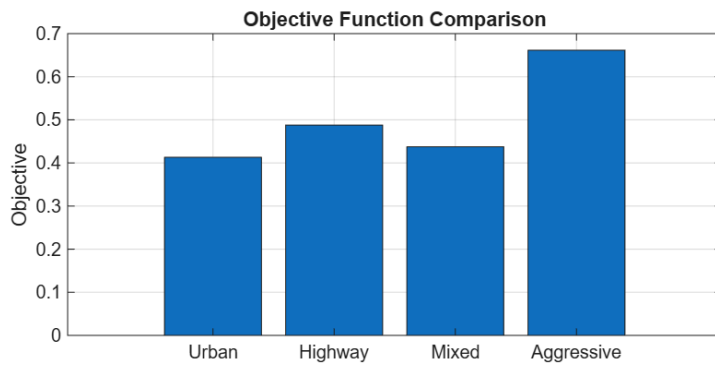


Figure 8. Final composite objective function scores for each optimized configuration.

The Urban profile achieved the lowest cost owing to its high specific efficiency (89.60 Wh/km) and minimal pack mass (183.12 kg). The Aggressive profile registered the highest value, a 60.1% increase relative to Urban, reflecting the combination of the largest pack mass, the highest current stress, and the highest specific consumption.

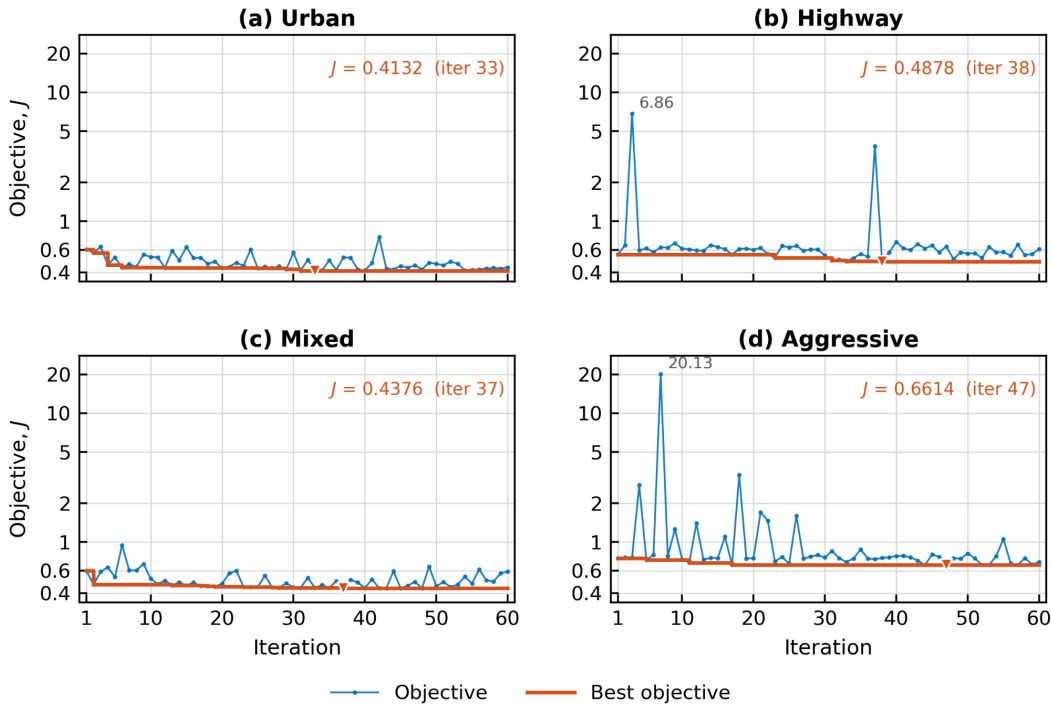


Figure 9. Convergence of the Bayesian optimization for each drive cycle: (a) Urban, (b) Highway, (c) Mixed, (d) Aggressive. Blue traces show the objective at each of the 60 function evaluations; orange traces show the best value found..

3.5. Behaviour of the Optimization Objective

Figure 9 shows the convergence histories of the Bayesian optimizer for the four drive cycles over 60 evaluations. The searches do not improve monotonically, as expected, because the acquisition function alternates between exploring new regions of the design space and exploiting previously successful configurations. Urban and Mixed produced relatively smooth trajectories, peaking at 0.75 and 0.94, whereas Highway and Aggressive returned several large spikes, reaching 6.86 and 20.13 respectively. These spikes correspond to candidate packs that violated one or more constraints and therefore incurred large penalties; the optimizer discarded them without losing the incumbent. The best objective values converged to 0.4132 (Urban, iteration 33), 0.4376 (Mixed, iteration 37), 0.4878 (Highway, iteration 38) and 0.6614 (Aggressive, iteration 47). The converged designs in Table 4 reveal two structural limitations of the objective itself. First, the thermal term is essentially inactive: temperature rise is negligible for every candidate, so one-fifth of the nominal weight does no work. Second, pack mass and estimated range depend on the design variables only through the product $N_s N_p C_{cell}$; once the current penalty is also inactive, the objective becomes nearly invariant along this manifold. Many distinct series-parallel arrangements therefore yield almost identical objective values, and only total pack energy is reliably identified. The results show: all four ranges fall within a 14 km band immediately above the 300 km constraint, and C_{cell} sits at its lower bound in three of the four cycles. The higher N_s values selected for the

Highway and Aggressive cycles should not, therefore, be read as uniquely optimal. Nothing in J rewards higher terminal voltage once the current limit is satisfied, apart from a second-order benefit through the effect of I^2R loss on E_{per-km} . Making N_s and N_p separately identifiable would require terms depending on each individually: a DC-bus voltage target, a per-string C-rate limit or a two-sided range penalty.

4. DISCUSSION

4.1. Transient Content, Not Distance, Governs Consumption

The results show that duty-cycle character, not distance, governs both energy use and pack size. Across four cycles covering nearly the same distance, specific consumption varied by a factor of 1.86, from 89.60 Wh/km on the Urban cycle to 166.97 Wh/km on the Aggressive cycle, while peak pack current rose by 80.9%, from 142.22 A to 257.22 A.

The mechanism is ohmic. Rapid, high-power acceleration forces large pack currents, and because loss scales as I^2R , these transients dissipate a disproportionate share of the drawn energy as heat that regenerative braking recovers only partially [2], [3], [5]. The ordering of consumption across the four cycles follows the ordering of peak current, not the ordering of average speed.

4.2. Design and Deployment Implications

The design consequence is substantial. Holding a common 300 km nominal range target, required pack energy grew from 27.47 kWh under the Urban duty cycle to 50.90 kWh under the Aggressive one, an 85.3% increase in pack mass. This matters for dense Indian cities, where stop-and-go traffic in Delhi, Mumbai, and comparable centres produces exactly the frequent high-power transients modelled here, and where localized cycles report the same gap against standardized international cycles [6]–[8]. A pack sized on a homologation cycle may be materially under-provisioned for real urban duty.

The same mechanism explains why real-world range so often falls short of manufacturer figures: two drivers covering identical distances draw very different amounts of energy depending on how they drive. Ride-hailing vehicles, delivery vans and urban logistics fleets accumulate acceleration events all day, and are correspondingly exposed to the current-driven losses identified here. The same argument extends to fleet and charging planning, where demand is usually estimated from average distance travelled. A bus route with heavy congestion and frequent stops can require substantially more capacity than a route of the same length run at uniform speed, so sizing on distance alone risks under-provisioning.

4.3. Identifiability of the Optimization Objective

A second contribution is diagnostic rather than numerical. Although the optimized designs exhibited different N_s values across duty cycles, these differences should not be interpreted as uniquely optimal series-cell configurations. The optimizer placed C_{cell} at its lower bound on three of four cycles and N_s at its upper bound on two. This behaviour is a property of the objective formulation rather than a search failure: pack energy, mass, and range all depend on the design variables through the product $N_s N_p C_{cell}$, while the

current, thermal, and state-of-charge penalties remain inactive at every converged design. Consequently, the optimization identifies the required total pack energy but does not uniquely identify its series–parallel architecture. Restoring an interior and physically identifiable optimum would require terms that depend on N_s and N_p separately, such as a DC-bus voltage target, a per-string C-rate limit, and a two-sided range target.

4.4. Limitations

Several simplifications bound these conclusions. Each candidate was evaluated over a single 16–18 km cycle that depletes roughly 5% of the pack, so range is a linear extrapolation at full depth of discharge and the state-of-charge constraint could never become active. The lumped thermal model returned a negligible temperature rise, leaving the thermal term inert. Road grade was fixed at zero, auxiliary load held constant, and battery ageing was outside scope. Only one optimization run was performed per cycle, with no seed repeats and no equal-budget random-search baseline, so convergence stability and sensitivity to the initial surrogate remain untested. Velocity-tracking RMSE was not retained in the logged output, so the composite objective cannot be fully decomposed from the data presented.

5. CONCLUSION

This work coupled a forward-facing MATLAB/Simulink powertrain and electro-thermal battery model to a Bayesian optimizer, sizing C_{cell} , N_s , and N_p independently for four drive cycles of matched distance but differing transient content, using 60 evaluations per cycle with a Gaussian-process surrogate and expected-improvement acquisition.

Specific energy consumption spanned 89.60 to 166.97 Wh/km and peak pack current 112.55 to 257.22 A. Holding the same 300 km target, required pack energy rose from 27.47 to 50.90 kWh, an 85.3% increase in pack mass. The penalty-augmented objective suppressed over-design: all four configurations converged within a 14 km band immediately above the constraint, none carrying more than 4.4% surplus range.

The formulation itself proved partly degenerate. The range constraint was the only active constraint, and pack architecture beyond total energy remained weakly identified, so the series–parallel split reported here should be read as one point on a near-flat manifold rather than a unique optimum.

Future work should validate the framework against measured Indian urban drive cycles, repair and validate the electro-thermal model so the thermal terms carry weight, incorporate battery-ageing cost into the objective, and couple a reformulated objective to the full Simulink model to confirm that the optimizer selects interior N_s and N_p values.

Code Availability

The MATLAB and Simulink code developed for this study is publicly available on GitHub at:

<https://github.com/SaiSamyukthaPammi/EV-Battery-Pack-Optimization.git>

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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