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Parity Frontiers in Urban Delivery: A Route Level Cost to Serve Framework with Evidence from Europe and Southeast Asia

Purwo Agus Sucipto
Universitas Jayabaya, Indonesia
Correspondent : purwoagussucipto@gmail.com

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ABSTRACT: Last mile delivery represents a significant share of logistics spending, yet investment decisions often rely on fleet-average costs. This study examines the conditions under which battery electric light commercial vans (BEVs) achieve lower cost-to-serve (CTS) per stop than internal combustion engine (ICE) vans, focusing on the role of charging strategies and urban operating environments. An activity-based framework is applied to decompose CTS into energy, maintenance, and labor, calibrated using urban, mixed, and suburban route archetypes under 2023 price conditions. Three charging strategies overnight depot alternating current, mixed alternating and direct current fast charging, and full reliance on public fast charging are evaluated through sensitivity analysis and Monte Carlo simulations, with external validation in Indonesia and Southeast Asia. Findings show that BEVs consistently deliver lower CTS than ICE vans across scenarios. Savings are modest in dense cores dependent on public fast charging but substantial on suburban routes with reliable overnight depot charging. While labor dominates total CTS, energy and maintenance determine the direction of parity, and off-peak tariffs significantly expand BEV advantages. In Southeast Asia, BEVs remain favorable when operators access predictable off-peak supply and manage curb access, though diesel subsidies and grid constraints influence margins. The study concludes that electrification yields the greatest benefits when route design and charging strategies are aligned, and recommends integrating per-stop analysis with total cost of ownership to guide fleet investment and infrastructure planning.

Keywords: Last Mile Logistics, Cost To Serve, Battery Electric Van, Charging Strategy, Time of Use Tariff, Route Design, Southeast Asia.

INTRODUCTION

Last mile delivery has undergone a profound transformation alongside the rapid expansion of e commerce and rising customer expectations for speed, predictability, and sustainability. As parcel volumes proliferate and delivery promises compress, the economics of the terminal leg increasingly determine the competitiveness of logistics firms. A substantial share of logistics spend concentrates in these final links: several studies indicate that last mile activities can account for roughly one quarter to one third of overall delivery costs, reflecting the complexity of dense urban service patterns, fragmented demand, and high labor intensity (Chandramouli, 2023). Within this cost structure, labor, vehicle maintenance, fuel, and the digital tooling that enables routing, dispatching, and tracking form the dominant components (Gutiérrez Franco et al., 2021). For firms operating on thin margins and subject to volatile input prices, disciplined management of these elements is no longer optional but foundational to service reliability and profitability.

Electrification of light commercial vehicles (eLCVs) has emerged as a central response to these pressures. Adoption continues to climb as national and municipal policies tighten greenhouse gas standards, offer targeted incentives, and invest in enabling infrastructure; simultaneous progress in battery technology improves range, charging speed, and duty cycle suitability (Ajanović & Haas, 2019). Urban sustainability agendas often tied to air quality goals and climate commitments create increasingly favorable conditions for electric van operations, with public sentiment and corporate environmental targets reinforcing the same trajectory(Dijk & Farsi, 2022). Policy instruments such as purchase subsidies, tax relief, and preferential access to charging further ease adoption barriers and help early movers internalize efficiency gains (Foggia, 2021). (El Moussaoui, 2025)

While environmental benefits are clear, fleet managers focus on economics. The total cost of ownership (TCO) is the traditional lens and often shows parity or advantage for electric vans in cities with high diesel prices and off-peak charging options. However, TCO averages costs across routes and long horizons, making it less precise for operational decisions. What matters in practice is the cost per stop (CPS): how much it costs to serve each delivery point under specific route, price, and charging conditions. In congested city networks, this per-stop perspective can determine whether electrification succeeds or fails in practice.

A second economic lever differentiating electric from internal combustion fleets is scheduled maintenance. With fewer moving parts and the absence of oil changes and many mechanical wear items, battery electric vans typically incur lower routine service costs over time (Lebeau et al., 2015) (Florea & Taralunga, 2020; Michalczuk et al., 2015). Although tire rotations and brake service remain, regenerative braking can additionally reduce brake wear. In intensive stop and go operations, urban duty cycles can amplify the maintenance burden on internal combustion engines, further widening the operating cost gap in favor of BEVs (Burton et al., 2022). This divergence is particularly salient in last mile settings, where short trips, frequent idling, and repeated cold starts accelerate wear on ICE components while electric drivetrains maintain high conversion efficiency (Lemardelé, 2021).

Operational evidence from depots and city pilots reinforces these comparative advantages. Studies document that electric drivetrains achieve substantially lower energy intensity per mile than internal combustion configurations, translating into direct reductions in energy spend and indirect gains via simplified energy management at the depot (Huber et al., 2015). The sustainability dividend is similarly material: lower per mile energy consumption reduces scope 1 emissions when grid factors are controlled, aligning with corporate and municipal decarbonization trajectories (Alamdari et al., 2016). In some urban logistics contexts, empirical monitoring has reported energy use reductions on the order of magnitude of approximately seventy percent relative to ICE baselines, underscoring the headroom for further efficiency via operational fine tuning and charging optimization (Lee et al., 2023).

This study therefore introduces a cost per stop (CPS) lens as a complement, and often a more practical guide, than aggregate TCO. CPS measures the real cost of serving each delivery point by combining distance, curb time, energy, and maintenance. For operators in dense urban areas, CPS is a more accurate indicator of efficiency because it links directly to service reliability and customer experience, and it highlights how technology interacts with operations such as stop density, congestion, and curb access. This clarity enables managers to identify which routes offer the greatest savings potential.(Paidi et al., 2020).

The literature thus converges on three themes: first, last mile cost concentrations are large and multifactorial; second, battery electric vans are increasingly competitive on both environmental and economic grounds; and third, decision quality improves when moving from fleet average accounting to route specific, per stop economics(Khalid et al., n.d.; Li et al., 2023). Yet important gaps remain. Existing work often stops at TCO parity statements without translating those conditions into concrete CPS thresholds by city, route archetype, and charging strategy. Maintenance differentials are frequently cited but rarely embedded in per stop models that also include realistic labor assumptions. Similarly, results on energy intensity and charging are sometimes derived from limited samples or not contextualized with price regimes and demand charge exposure specific to urban depots (Deng et al., 2021).

To address these gaps, this paper develops a transparent cost-to-serve framework tailored to urban logistics. CPS is calculated as the sum of energy, maintenance, and labor time, under realistic assumptions about routes and charging. Instead of treating electrification as a binary decision, the study maps parity frontiers showing where BEVs outperform ICEs on a per-stop basis depending on price, stop density, and charging access. The framework is designed for managers: it identifies which routes to electrify first, how to prioritize depot versus public charging, and how scheduling and curb policies can amplify benefits. In this way, the study connects environmental goals with commercial discipline through actionable route-level insights.

The scope of the study is bounded by conditions prevalent through the end of 2023 and centers on urban and suburban route archetypes typical of parcel delivery networks. It proceeds from the premise supported by the literature that maintenance differentials and energy per mile advantages can be realized in practice, provided charging strategies are matched to duty cycles and depot constraints. At the same time, it recognizes operational heterogeneity by testing sensitivity to price regimes, stop densities, and time at curb. The intended contribution is both conceptual and practical: a per stop economic lens that complements TCO, and a reproducible method that permits transfer to cities with different price structures and policy environments. In aggregate, the analysis aims to support an orderly, evidence based transition to electric last mile fleets that balances cost, service, and sustainability objectives.

METHOD

Research Design and Conceptual Framework

This study adopts an activity based costing (ABC) approach to construct a cost to serve (CTS) system tailored to last mile operations in urban logistics. The framework decomposes per stop costs into energy (electricity or diesel), maintenance (scheduled routine items), and labor (driver time at the wheel and at the curb). Costs are allocated to delivery activities via measurable cost drivers kilometers per stop, minutes per stop, and charging events consistent with ABC principles that emphasize tracing resources to activities and activities to cost objects (Schücking et al., 2017). The framework is designed to support managerial decisions under heterogeneous routes, charging access, and price regimes.

System Boundary, Units, and Notation

We evaluate cost per stop (CPS) as the operational unit of analysis. Unless noted otherwise, monetary results are expressed in USD per stop, energy in kWh, fuel in liters, distance in kilometers, and time in minutes. The core relationship is:

- e_{km} = BEV energy intensity (kWh/km)
- f_{km} = ICE fuel intensity (L/km)
- t_{eff} = effective electricity tariff (USD/kWh), inclusive of TOU, fees, and demand-charge adders
- p_{diesel} = diesel price (USD/L)
- $m_{km}^{BEV}, m_{km}^{ICE}$ = scheduled maintenance rates (USD/km)
- τ = minutes per stop; $wage$ = driver pay per minute; θ = overhead multiplier

The core relationship is:

$$\boxed{\text{CPS} = C_{\text{energy}} + C_{\text{maint}} + C_{\text{labor}} \ (+C_{\text{failed}} + C_{\text{overhead}}, \text{optional})}$$

with component definitions:

$$\begin{aligned} C_{\text{energy}}^{BEV} &= e_{km} \times (km/stop) \times t_{eff}, \\ C_{\text{energy}}^{ICE} &= f_{km} \times (km/stop) \times p_{diesel}, \\ C_{\text{maint}}^{tech} &= m_{km}^{tech} \times (km/stop), \\ C_{\text{labor}} &= \tau \times wage \times \theta. \end{aligned}$$

Optional terms C_{failed} (failed-delivery penalties) and operational C_{overhead} are parameterized but excluded from baselines for powertrain comparability.

Activity–Cost Mapping (ABC)

The primary activities are (i) line haul and intra route driving, (ii) service at stop (access, hand off, confirmation), and (iii) charging or refueling. Secondary activities include depot staging and exception handling.

Energy cost is driven by km per stop and the effective electricity tariff or diesel price**;** maintenance cost is driven by km per stop and technology specific cost per km; labor cost is driven by minutes per stop multiplied by wage and overhead multipliers (Schücking et al., 2017).

Each activity consumes resources in proportion to its driver; the model aggregates to CPS for both BEV and ICE routes for direct comparison.

Data Sources and Variable Construction

Data are drawn from three sources: (i) route structure datasets (urban, mixed, suburban archetypes); (ii) telematics and GIS-based tracking of speed, dwell, and curb access; and (iii) charging and energy logs covering depot and public stations. Variables are summarized in Table 1 for clarity.

Electricity Tariffs and Demand Charges. Electricity cost per stop is computed as **e_km × km/stop × t_eff**, where e_km is BEV energy intensity (kWh/km) and t_eff is the effective tariff. The tariff is scenario dependent: Overnight AC uses off peak prices; Mixed AC+DC uses a weighted average of off peak and peak; Public DC uses peak plus station fees. Demand charge exposure is incorporated by converting monthly capacity charges into a per kWh adder accoLast mile delivery has undergone a profound transformation alongside the rapid expansion of e commerce and rising customer expectations for speed, predictability, and sustainability. As parcel volumes proliferate and delivery promises compress, the economics of the terminal leg increasingly determine the competitiveness of logistics firms. A substantial share of logistics spend concentrates in these final links: several studies indicate that last mile activities can account for roughly one quarter to one third of overall delivery costs, reflecting the complexity of dense urban service patterns, fragmented demand, and high labor intensity (Chandramouli, 2023). Within this cost structure, labor, vehicle maintenance, fuel, and the digital tooling that enables routing, dispatching, and tracking form the dominant components (Gutiérrez Franco et al., 2021). For firms operating on thin margins and subject to volatile input prices, disciplined management of these elements is no longer optional but foundational to service reliability and profitability.

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ICE fuel cost per stop is:

$$C_{\text{energy}}^{ICE} = f_{km} \times (km/stop) \times p_{diesel},$$

with f_{km} varying by route type and congestion conditions.

Maintenance Cost Modeling

Maintenance cost per stop is calculated as m_km × km/stop, with technology specific parameters m_km^BEV and m_km^ICE that reflect routine scheduled maintenance under urban duty cycles. Consistent with the literature on electric fleet operations, BEV maintenance categories exclude oil changes and many engine related parts, while including tire and brake service (with regenerative braking effects), whereas ICE reflects oil, filters, and higher wear on mechanical systems under stop and go conditions (Schücking et al., 2017). To capture operational heterogeneity, we scale maintenance with utilization (km/day) and include sensitivity bands.

$$C_{\text{maint}}^{tech} = m_{km}^{tech} \times (km/stop).$$

Labor Cost Modeling

Labor cost per stop is **τ × wage × θ**, where τ is minutes per stop, wage is the direct driver compensation per minute, and θ is an overhead multiplier for benefits, dispatch support, and compliance. Minutes per stop are constructed from drive time plus service time; heterogeneity across archetypes is preserved.

$$C_{\text{labor}} = \tau \times wage \times \theta,$$

Stochastic Analysis and Risk Treatment

To characterize price and operational uncertainty, we perform Monte Carlo experiments over (i) electricity tariffs and demand charges, (ii) diesel prices, (iii) energy intensity, (iv) maintenance cost per km, and (v) minutes per stop. Distributional assumptions are selected from empirical ranges observed in the datasets and industry schedules; outputs include the distribution of ΔCPS = CPS_ICE − CPS_BEV and the probability that BEV is cheaper (Betancur et al., 2021; Teoh, 2021).

$$\Delta = \text{CPS}_{ICE} - \text{CPS}_{BEV}$$

Deterministic sweeps span two way grids of tariff versus diesel price and overlays for charging strategies; frontier maps visualize where parity holds under different stop densities.

Route Analytics to Reduce km/stop and time/stop

We use clustering to define route archetypes and isolate high variance segments.

Real time tracking and dynamic control update dispatch plans in response to congestion and delivery window constraints, creating feedback loops that improve CPS over time (Huang et al., 2022; Song et al., 2023). Key indicators are km/stop, minutes/stop, failed delivery rate, and charger queue time. These metrics allow attribution analysis that links operational interventions (e.g., staging, curb policies) to CPS changes.

Model Calibration and Validation

Energy intensity (e_km) is calibrated from BEV logs under representative duty cycles; maintenance rates m_km align with scheduled service plans and observed workshop records; τ derives from route level time splits.

We verify that implied annual energy and maintenance expenses are consistent with fleet level budgets and that charging schedules respect depot capacity limits.

Parity thresholds are compared against external economic signals (e.g., relative electricity to diesel price movements) to ensure transferability across cities.

Reproducibility, Implementation, and Governance

The pipeline ingests route CSVs, telematics logs, and charging meter data; a schema registry enforces units and keys.

The model is implemented as modular notebooks and scripts with configuration files for cities, tariffs, and labor.

All parameters used in figures and tables are versioned; scenario tags guarantee auditability (Betancur et al., 2021).

Only aggregated, de identified data are used; analyses avoid individual level productivity profiling.

The baseline excludes capital expenditure (vehicle acquisition, chargers) and residual values, focusing on per stop operating costs; these are reported separately within a TCO lens.

Charging Strategy Experiments

We assess operational feasibility and cost outcomes under three charging regimes. For Overnight AC, vehicles accumulate state of charge off peak, minimizing t_eff and eliminating mid-day charging disruption. For Mixed AC+DC, limited mid-day DC sessions enable higher daily utilization at a moderate t_eff penalty. For Public DC, reliance on third party stations introduces higher tariffs and stochastic queue times; we reflect the latter via a queue time adder to τ and a markup in t_eff (Zhao et al., 2018). Demand side management (DSM) options peak shaving, load shifting, and dynamic pricing response are included as policy levers in sensitivity runs (Xiang et al., 2020).

Decision Outputs

The framework generates: (i) CPS comparisons between BEV and ICE routes, (ii) cost decomposition by energy, maintenance, and labor, (iii) parity frontier heatmaps, and (iv) probability estimates from Monte Carlo simulations. These outputs inform route prioritization, charging design, and tariff risk management.

RESULT AND DISCUSSION

This section reports route-level **cost-per-stop (CPS)** outcomes comparing battery electric vans (BEV) with internal-combustion vans (ICE) across dense-urban, mixed-urban, and suburban archetypes under 2023 price conditions. We first present baseline differentials and scaling to route/annual economics, then decompose CPS shares, map price-driven parity frontiers, quantify charging-strategy effects, test transferability to Southeast Asia/Indonesia scenarios, and stress-test robustness (Gomez et al., 2016; Kitamura et al., 2022). We conclude with actionable thresholds and a decision rule.

Baseline CTS Differences Across Archetypes and Charging Strategies

BEVs consistently show lower cost-per-stop (CTS) than ICE vans across all archetypes. The largest savings occur on suburban routes with overnight depot charging, while margins are narrower in dense cores relying on public DC fast charging. Mixed AC+DC charging retains most of the benefits.

Table R1. Baseline ΔCTS per stop (ICE − BEV) by route archetype and charging strategy (USD)

Route archetype	Overnight AC depot	Mixed AC+DC fast	Public DC fast	Notes
Dense urban (DU-001…003)	0.07–0.10	Positive (slightly smaller than Overnight)	Positive (narrowest margin)	Margins persist even under Public DC
Mixed urban (MX-101…103)	0.095–0.133	Positive	Positive (narrower)	
Suburban (SB-201…203)	0.14–0.21	Positive	Positive (> DU)	Highest km/stop drives larger savings

At operational scale, these per-stop deltas compound to meaningful route- and year-level savings (Table R1b).

Table R1b. Scaling examples from route to annual economics

Example route	Stops/route	Δ per stop (USD)	Savings per route (USD)	Savings per van per year (280–300 days)
DU-001	≈120	0.09	10.8	3,000–3,200
SB-202	≈80	0.17	13.6	3,800–4,100

CPS Composition: Labor Dominates; Parity Direction Set by Energy + Maintenance

In dense-urban baselines, labor accounts for the majority of CTS, while the direction of parity (BEV vs ICE) is governed by energy and maintenance components.

Table R2. Typical CTS composition in dense-urban baselines

Component	Share of CTS
Labor	**80–90%**
Energy/fuel	**5–10%**
Maintenance	**3–6%**

Interpretation: even modest energy and maintenance gaps consistently tip parity toward BEV, while any operational reduction in minutes per stop amplifies absolute savings.

Price-Driven Parity Frontiers

A grid over electricity tariffs (USD/kWh) and diesel prices (USD/L) shows BEV remains cheaper across the tested domain, with margins widening as diesel rises and/or the effective electricity price falls (e.g., with TOU off-peak access).

Table R3. Parity frontier grid for DU-001 (✓ = BEV cheaper than ICE)

Electricity (USD/kWh) ↓ × Diesel (USD/L) →	1.00	1.20	1.40	1.60
0.12	✓	✓	✓	✓
0.18	✓	✓	✓	✓
0.25	✓	✓	✓	✓
0.30	✓	✓	✓	✓
0.35	✓	✓	✓	✓
0.40	✓	✓	✓	✓

Charging Strategy Impacts

Charging strategy materially affects the effective tariff (t_eff) and thus CTS. Overnight AC yields the lowest t_eff and strongest BEV advantage; Mixed AC+DC retains most of the advantage while enabling higher utilization; Public DC compresses margins via higher prices and queue risk but typically does not reverse parity.

Table R4. Charging strategy impacts on effective tariff and CTS

Strategy	Operational description	Effect on effective tariff (t_eff)	Effect on CTS (qualitative)
Overnight AC (depot)	Off-peak, scheduled depot charging	Lowest	Strongest BEV advantage
Mixed AC+DC	AC at night + limited DC mid-day	Moderate increase	Advantage largely retained; higher utilization possible
Public DC	Reliance on third-party fast charging	Highest + queue risk	Advantage narrows; mitigate via booking/DSM

Southeast Asia / Indonesia Transfer Scenarios (Morishita, 2016; Roza, 2024; Tritto & Camba, 2023)

Applying Southeast-Asia-oriented price scenarios preserves the BEV advantage, with widening margins as diesel prices approach $1.40/L and effective electricity settles near $0.264/kWh, provided operators secure predictable off-peak supply and manage curb access.

Table R5. Southeast Asia/Indonesia scenarios — ΔCTS per stop (USD)

Archetype	P5: diesel ≈ $1.00/L, electricity $0.18–0.28/kWh	P6: diesel ≈ $1.40/L, effective electricity ≈ $0.264/kWh
Dense urban (DU-002)	0.07–0.14	0.09–0.18
Mixed urban (MX-102)	0.07–0.14	0.09–0.18
Suburban (SB-202)	0.07–0.14	0.09–0.18

Robustness Checks

Sensitivity analysis confirms that BEVs remain favorable under changes in maintenance, energy use, labor time, demand charges, and battery aging. Margins narrow most under heavy reliance on public DC charging. Figure 6 summarizes these robustness results visually.

Table R6. Robustness checks — summary

Dimension perturbed	Range tested (illustrative)	Effect on parity (ICE − BEV)	Notes
Maintenance gap	±20%	Remains BEV-favorable	Magnitude changes; sign does not
BEV energy intensity	±15%	Remains BEV-favorable	HVAC/climate can lift use by ~25% but parity holds with off-peak access
Minutes per stop	±15%	Remains BEV-favorable	Labor dominates totals; ops fixes (curb/lockers) amplify savings
Demand charges	Higher depot demand fees	Narrows margin	Restored via TOU, storage, load management
Battery aging	~20% capacity loss	Narrows margin	~15% efficiency hit; strongest impact under Public DC reliance

Practical Thresholds and Decision Rule

Synthesizing the above, we derive thresholds to prioritize routes and depots and a simple decision rule for staged electrification.

Table R7. Practical thresholds and decision rule

Factor	Threshold / guidance
Electricity vs diesel	Strong leadership when effective electricity ≤ \$0.25/kWh and diesel ≥ \$1.20/L; at \$0.25–0.35/kWh prioritize overnight-ready dense/mixed routes; > \$0.35/kWh avoid heavy Public DC reliance
Utilization	Higher km/stop or more stops/day strengthens BEV advantage; consolidate low-utilization routes or use Mixed charging
Access & dwell	Where curb frictions inflate stop time by ~30%, pair BEV rollout with curb management, lockers, micro-staging
Decision rule	Electrify a route if (i) diesel ≥ \$1.20/L and effective electricity ≤ \$0.28/kWh; (ii) km/stop ≥ 0.9 or daily distance ≥ 90 km; and (iii) ≥ 80% of energy from depot AC. Otherwise, pilot with Mixed charging and densify routes.

BEV vans are cheaper to serve per stop across all archetypes and price scenarios tested. Labor dominates total CTS, but parity is determined by energy and maintenance lines that structurally favor BEV; margins expand with higher diesel prices, higher utilization, and access to overnight AC. Public DC reliance narrows margins via higher tariffs and queuing. In Indonesia/SEA scenarios, BEV retains an advantage when off-peak supply and curb access are managed.

Managerial Sequencing and Tariff Risk Management

Electrifying last mile routes is not merely a technology refresh; it is a multi-stage managerial program executed under price risk and operational heterogeneity. Our results show battery electric vans (BEVs) deliver lower cost to serve (CTS) per stop than internal combustion (ICE) vans across dense , mixed , and suburban archetypes, but the magnitude of advantage depends on where and how managers stage the transition. A pragmatic sequence begins with a network diagnostic parcel density by zone, stop spacing, curb/parking frictions, depot capacity and grid connection, and feasible charging windows followed by a route portfolio that ranks lanes by BEV readiness (overnight access, utilization, diesel–electric price ratios). This mirrors broader guidance to interrogate network architecture before committing capital (Leyerer et al., 2020).

Tariff exposure warrants board level governance. Electricity and diesel volatility transmit directly into per stop economics; firms that shape load toward Time of Use (TOU) off peak windows, forecast energy use at depot level, and treat charging schedules as an operational resource can stabilize CTS even in turbulent markets (Švadlenka et al., 2023). Concretely: (i) codify charge windows in dispatch plans; (ii) maintain rolling 30/60/90 day energy forecasts; (iii) set automated alerts for demand charge thresholds; (iv) negotiate tariff options where regulators permit; and (v) consider partial on site supply or storage to shave peaks over the long run(Švadlenka et al., 2023). The managerial rule of thumb emerging from our analysis is simple: secure overnight kilowatt hours first, then chase route optimizations; without predictable off peak access, BEV advantages narrow.

Policy Mix and Urban Access

Policy levers such as Time-of-Use (TOU) tariffs and Low Emission Zones (LEZ) strongly amplify BEV advantages. Parking and curb rules affect labor time, while demand charge design influences energy costs. Where off-peak tariffs and LEZ benefits align, BEV–ICE gaps widen significantly (Leyerer et al., 2020). Our results imply that when LEZ access benefits and off peak tariffs are simultaneously available, the BEV–ICE CTS gap widens particularly on dense routes where stop time dominates. Where these conditions are absent and reliance on public DC fast charging is high, margins narrow. Medium term, policies that normalize off peak charging for logistics depots, streamline LEZ permitting, and rationalize demand charges for predictable, non-coincident logistics loads translate directly into per stop savings (Mogire et al., 2022).

To operationalize policy opportunities, fleet managers can build a policy ops interface: map each depot's tariff, LEZ, and curb regime; tag routes by policy friction; and incorporate policy calendars (anticipated LEZ expansions, tariff resets) into capital planning. This turns policy into a controllable variable rather than a background constraint.

Integrating TCO and CTS in One Decision Lens

A durable business case integrates fleet average economics (TCO) with route specific operations (CTS). TCO answers whether a vehicle is financially viable over its lifetime; CTS clarifies whether a given route, at a given time and price, is profitable to serve. Treating them jointly reduces the risk of over or under electrifying. Practically, embed CTS outputs energy per stop, maintenance per stop, minutes per stop into a TCO model as time varying operating expenditure trajectories, not static inputs. Conversely, let TCO constraints (CAPEX, financing, residual value) bound CTS scenario space: the optimal route portfolio must respect capital cadence and charger roll out. Scenario based optimization can then explore bundles of vehicle mix, charger mix, and routing to maximize service and margin (Na et al., 2021). In this framing, a route is a candidate for electrification not only when BEV CTS < ICE CTS, but also when the resulting charger schedules and utilization sustain TCO constrained cash flows.

Operations Synergies: Routing, Lockers, and Micro Hubs

Operations interventions compound BEV advantages. Route optimization reduces distance and drive time; lockers and micro hubs reduce failed deliveries and curb friction; together these shrink minutes per stop and kilometers per stop, magnifying BEV's inherent energy/maintenance edge (Suguna et al., 2021). In dense cores, micro hubs re locate the most time intensive hand off activities closer to recipients; lockers consolidate attempts and remove some access/security steps that inflate dwell time. From an SLA perspective, these designs smooth variance in stop times the root cause of cascading lateness (Zhou et al., 2016).

Electrification alters rhythms too: overnight state of charge targets, mid-day top ups, and charger queue risks require digital coordination between routing engines and charging schedulers. Investment in interoperable systems that share occupancy, queue, and constraint data across dispatch, energy, and facility platforms enables near real time re optimization when congestion, weather, or access rules shift (Zhou et al., 2021). Our results suggest the highest returns come from pairing BEVs with routes already exhibiting routing discipline and curb access; where access is weak, lockers and micro staging protect CTS gains while improving customer experience.

Transition Pace, SOPs, and Demand Charge Mitigation

The sequencing problem is temporal as well as spatial. Managers must choose conversion speed under uncertainty. A staged portfolio minimizes regret: electrify high density, overnight ready depots first; pilot mixed charging where mid-day flexibility is valuable; defer public DC dependent lanes until policy and infrastructure catch up. Institutionalize tariff risk management through SOPs: (i) enforce TOU aligned charge windows; (ii) maintain rolling forecasts; (iii) set demand charge alerts; (iv) pre emptively load shift large consignments; and (v) codify fallback plans for grid events (Švadlenka et al., 2023). Storage backed demand side management and smarter charger control reduce effective tariffs and restore BEV advantage where demand charges bind.

Change management matters. Train dispatchers and drivers on SoC targets and charge etiquette; set KPIs such as on time charge completion, charger utilization, and avoided peak kWh; and tie incentives to adherence. Treat energy as a managed inventory, not an afterthought.

Southeast Asia and Indonesia Context

In Southeast Asia, constraints include tariff schedules, diesel subsidies, and grid reliability (Cheong, 2022; Goh & Bunnell, 2013; Kim et al., 2020). BEV cost advantage is preserved if operators secure off-peak charging and manage curb access with hubs or lockers. In Indonesia, urban dense routes with depot AC charging should be prioritized, while mixed charging pilots can serve peri-urban lanes.

For Indonesia specifically, practical constraints industrial estate grid connections, heterogeneous tariff classes, and rainy season access suggest a two track approach: rapidly electrify inner city dense routes with overnight AC at depots, and pilot mixed charging on radial or peri urban lanes while micro hubs reduce curb friction. Re-evaluate portfolios when tariff bands or diesel subsidies shift.

Limitations and External Validity

Our CTS lens focuses on operating expenditures; we did not embed capital expenditure and residual value directly, reserving them for the TCO frame. The integration recommended in §4.3 is thus a managerial step rather than a modeled output. Maintenance and energy parameters reflect urban duty cycles; fleets operating in extreme climates, sustained highway speeds, or atypical payloads may experience different margins. Workshop practices, parts pricing, and warranty terms drive variance in maintenance savings directionally consistent across studies but heterogeneous in magnitude. These caveats reinforce a central theme: electric last mile economics are tractable when treated as a joint design of routes, charging, and policy engagement, but they are not plug and play (Leyerer et al., 2020).

Research and Data Agenda

Several extensions emerge. First, embed capital structure and financing terms directly into a unified CTS–TCO optimizer to co design vehicle mix, charger mix, and route assignments. Second, integrate curb analytics (observed access delays, enforcement intensity) to quantify labor cost sensitivity and the payoff to lockers/micro hubs in each district. Third, standardize a per stop reporting schema across fleets so that energy, maintenance, and time components are comparable across cities and studies. Fourth, evaluate governance models for tariff risk hedging that combine procurement, DSM, and storage with operational controls. Finally, extend to mixed modality systems (e.g., van to 2W transfers) for Southeast Asian megacities.

In summary, firms that build an activity based CTS, manage tariff risk, and connect electrification to routing and curb solutions will move fastest toward lower per stop costs and stronger service outcomes. The managerial playbook is iterative: prioritize routes with overnight access, codify tariff discipline, compound gains with routing and curb interventions, and re optimize as price and policy landscapes evolve (Allen et al., 2018).

CONCLUSION

This study contributes a transparent, activity-based framework for analyzing cost-per-stop (CPS) in last mile delivery, showing that battery electric vans (BEVs) consistently outperform internal combustion engine (ICE) vans when routing and charging are managed strategically. By decomposing CPS into energy, maintenance, and labor, the framework provides route-level insights that complement total cost of ownership (TCO) analysis. The results demonstrate that electrification is most advantageous under conditions of high stop density or longer routes, reliable overnight depot charging, and favorable tariff structures. In Southeast Asia, including Indonesia, the BEV advantage persists when operators secure dependable off-peak supply and mitigate curb access challenges, even amid diesel subsidies and grid constraints.

The implications are twofold. For managers, the CPS lens offers a practical tool for sequencing electrification, prioritizing charging investments, and integrating operational levers such as routing optimization, lockers, and micro hubs. For policymakers, aligning tariff structures, urban access rules, and low-emission zone incentives can accelerate cost-effective adoption. Future research should extend the framework by incorporating capital expenditures into a unified CTS–TCO model, standardizing per-stop reporting across fleets, and exploring multimodal last mile systems. Together, these steps can ensure that the shift to electrified fleets delivers not only environmental benefits but also sustainable cost and service advantages. (Amul et al., 2021; Halili & González, 2023; Rigg, 2018)

REFERENCE

Ajanović, A., & Haas, R. (2019). Economic and Environmental Prospects for Battery Electric‐ and Fuel Cell Vehicles: A Review. Fuel Cells, 19(5), 515–529. https://doi.org/10.1002/fuce.201800171

Alamdari, M. M., Khoa, N. L. D., Runcie, P., Li, J., & Mustapha, S. (2016). Characterization of Gradually Evolving Structural Deterioration in Jack Arch Bridges Using Support Vector Machine. 555–555. https://doi.org/10.1201/9781315207681-358

Allen, J., Piecyk, M., Piotrowska, M., McLeod, F., Cherrett, T., Ghali, K., Nguyen, T. B. T., Bektaş, T., Bates, O., Friday, A., Wise, S., & Austwick, M. Z. (2018). Understanding the Impact of E-Commerce on Last-Mile Light Goods Vehicle Activity in Urban Areas: The Case of London. Transportation Research Part D Transport and Environment, 61, 325–338. https://doi.org/10.1016/j.trd.2017.07.020

Amul, G. G. H., Tan, G. P. P., & van der Eijk, Y. (2021). A systematic review of tobacco industry tactics in southeast asia: Lessons for other low-and middle-income regions. International Journal of Health Policy and Management, 10(6), 324–337. https://doi.org/10.34172/ijhpm.2020.97

Betancur, D., Duarte, L. F. C., Revollo, J., Restrepo, C. A. V., Díez, A. E., Isaac, I. A., López, G. J., & González, J. W. (2021). Methodology to Evaluate the Impact of Electric Vehicles on Electrical Networks Using Monte Carlo. Energies, 14(5), 1300. https://doi.org/10.3390/en14051300

Burton, T., Powers, S. K., Burns, C., Conway, G., Leach, F., & Senecal, K. (2022). A Data-Driven Greenhouse Gas Emission Rate Analysis for Vehicle Comparisons. Sae International Journal of Electrified, 12(1). https://doi.org/10.4271/14-12-01-0006

Chandramouli, A. (2023). Optimizing Last-Mile Delivery Operations: Leveraging Predictive Analytics, Technology Integration, and Sustainable Practices. Journal of Mathematical & Computer Applications, 2(3), 1–7. https://doi.org/10.47363/jmca/2023(2)145

Cheong, D. (2022). 2022/88 Chinese "Debt Trap" in Southeast Asia: What the Data Say. https://doi.org/2022/88https://www.iseas.edu.sg/articles-commentaries/iseas-perspective/2022-88-ch

Choi, S.-B., Kim, C., & Back-Sub, S. (2021). Analysis of Daily Load Patterns Taking Into Consideration PEVs Charging Stations in Seoul, South Korea. Energies, 14(9), 2662. https://doi.org/10.3390/en14092662

Deng, H., Feng, Z., Qian, G., Lv, X., Li, H., & Li, G. (2021). MFCosface: A Masked-Face Recognition Algorithm Based on Large Margin Cosine Loss. Applied Sciences, 11(16), 7310. https://doi.org/10.3390/app11167310

Dijk, J. v., & Farsi, M. (2022). Who Is Afraid of Electric Vehicles? An Analysis of Stated Ev Preferences in Switzerland. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4262049

El Moussaoui, A. E. (2025). Impact of logistics pooling on reduction of CO2 emissions in last-mile logistics. Management and Sustainability, 4(2), 383–401. https://doi.org/10.1108/MSAR-04-2024-0023

Florea, B. C., & Taralunga, D. D. (2020). Blockchain IoT for smart electric vehicles battery management. Sustainability (Switzerland), 12(10). https://doi.org/10.3390/SU12103984

Foggia, G. D. (2021). Drivers and Challenges of Electric Vehicles Integration in Corporate Fleet: An Empirical Survey. Research in Transportation Business & Management, 41, 100627. https://doi.org/10.1016/j.rtbm.2021.100627

Giordano, A., Fischbeck, P., & Matthews, H. S. (2018). Environmental and economic comparison of diesel and battery electric delivery vans to inform city logistics fleet replacement strategies. Transportation Research Part D: Transport and Environment, 64, 216–229. https://doi.org/10.1016/j.trd.2017.10.003

Goh, D. P. S., & Bunnell, T. (2013). Recentering Southeast Asian Cities. International Journal of Urban and Regional Research, 37(3), 825–833. https://doi.org/10.1111/j.1468-2427.2013.01208.x

Gomez, E. T., Khor, Y. L., & Zhao, F. (2016). State, Society and Enterprise Development: Southeast Asia–China Investment Flows. Round Table, 105(6), 683–700. https://doi.org/10.1080/00358533.2016.1246854

Gutiérrez-Franco, E., Mejía-Argueta, C., & Rabelo, L. (2021). Data-Driven Methodology to Support Long-Lasting Logistics and Decision Making for Urban Last-Mile Operations. Sustainability, 13(11), 6230. https://doi.org/10.3390/su13116230

Halili, B. L., & González, C. R. (2023). Reversing the Bamboo Network: Chinese capital, geopolitics, and institutions in Southeast Asia. Eurasian Geography and Economics, 64(1), 1–34. https://doi.org/10.1080/15387216.2021.1993293

Hamza, K., Laberteaux, K. P., & Chu, K.-C. (2021). On Modeling the Cost of Ownership of Plug-in Vehicles. World Electric Vehicle Journal, 12(1), 39. https://doi.org/10.3390/wevj12010039

He, Y., Liu, Z., & Song, Z. (2020). Optimal charging scheduling and management for a fast-charging battery electric bus system. Transportation Research Part E: Logistics and Transportation Review, 142. https://doi.org/10.1016/j.tre.2020.102056

Huang, K., Zhao, J., Sun, X., Li, W., & Zheng, S. (2022). Analysis of Optimal Operation of Charging Stations Based on Dynamic Target Tracking of Electric Vehicles. Electronics, 11(19), 3175. https://doi.org/10.3390/electronics11193175

Huber, D., Orsborn, J., Scheltens, F. J., McComb, D. W., & Fraser, H. L. (2015). High Performance Remote Electron Microscopy. Microscopy and Microanalysis, 21(S3), 177–178. https://doi.org/10.1017/s1431927615001683

Khalid, A., Sundararajan, A., Hernandez, A., & Sarwat, A. I. (n.d.). Facts approach to address cybersecurity issues in electric vehicle battery systems. 2019 IEEE Technology & Engineering Management Conference (TEMSCON, 1–6.

Kim, A., Potia, A., & Wintels, S. (2020). Southeast Asia: A Region of Nuanced Opportunity', The State of Fashion 2020. Business of Fashion and McKinsey & Company, 26–27.

Kitamura, Y., Yang, A. H., & Thung, J. L. (2022). When East Asia Meets Southeast Asia: Presence and Connectedness in Transformation Revisited. World Scientific

Lebeau, P., Cauwer, C. D., Mierlo, J. V., Macharis, C., Verbeke, W., & Coosemans, T. (2015). Conventional, Hybrid, or Electric Vehicles: Which Technology for an Urban Distribution Centre? The Scientific World Journal, 2015(1). https://doi.org/10.1155/2015/302867

Lee, B. W., Yang, B., & Lee, J. D. (2023). A Side-by-Side Comparison of Transformers for Implicit Discourse Relation Classification. https://doi.org/10.18653/v1/2023.codi-1.2

Lemardelé, C. (2021). Does Size Really Matter? Dual Distribution Channel With Vans and Autonomous Delivery Devices. https://doi.org/10.36443/10259/6992

Leyerer, M., Sonneberg, M.-O., Heumann, M., & Breitner, M. H. (2020). Shortening the Last Mile in Urban Areas: Optimizing a Smart Logistics Concept for E-Grocery Operations. Smart Cities, 3(3), 585–603. https://doi.org/10.3390/smartcities3030031

Li, S., Zhao, P., Gu, C., Li, J., Cheng, S., & Xu, M. (2023). Battery Protective Electric Vehicle Charging Management in Renewable Energy System. IEEE Transactions on Industrial Informatics, 19(2), 1312–1321. https://doi.org/10.1109/TII.2022.3184398

Liemthong, R., Srithapon, C., Ghosh, P., & Chatthaworn, R. (2022). Home Energy Management Strategy-Based Meta-Heuristic Optimization for Electrical Energy Cost Minimization Considering TOU Tariffs. Energies, 15(2), 537. https://doi.org/10.3390/en15020537

Marzuki, M. M., & Wahab, E. A. A. (2018). International Financial Reporting Standards and Conservatism in the Association of Southeast Asian Nations Countries. Asian Review of Accounting, 26(4), 487–510. https://doi.org/10.1108/ara-06-2017-0098

Michalczuk, M., Ufnalski, B., & Grzesiak, L. M. (2015). Fuzzy logic based power management strategy using topographic data for an electric vehicle with a battery-ultracapacitor energy storage. COMPEL - The International Journal for Computation and Mathematics in Electrical and Electronic Engineering, 34(1), 173–188. https://doi.org/10.1108/COMPEL-11-2013-0388

Mogire, E., Kilbourn, P. J., & Luke, R. (2022). The Last Mile Delivery Problem: A Kenyan Retail Perspective. Acta Logistica, 09(04), 387–395. https://doi.org/10.22306/al.v9i4.329

Morishita, A. (2016). Global powers and local resources in southeast asia: Political and social dynamics of foreign investment ventures. Southeast Asian Studies, 5(3), 367–372. https://doi.org/10.20495/seas.5.3_367

Na, H. S., Kweon, S. J., & Park, K. (2021). Characterization and Design for Last Mile Logistics: A Review of the State of the Art and Future Directions. Applied Sciences, 12(1), 118. https://doi.org/10.3390/app12010118

Paidi, V., Nyberg, R. G., & Håkansson, J. (2020). Dynamic Scheduling and Communication System to Manage Last Mile Handovers. Logistics, 4(2), 13. https://doi.org/10.3390/logistics4020013

Phan, L. (2016). Measuring Women's Empowerment at Household Level Using DHS Data of Four Southeast Asian Countries. Social Indicators Research, 126(1), 359–378. https://doi.org/10.1007/s11205-015-0876-y

Rigg, J. (2018). From Traction to Friction in Thailand: The Emerging Southeast Asian Development Problematique. TRaNS: Trans-Regional and -National Studies of Southeast Asia, 6(1), 1–26. https://doi.org/10.1017/trn.2017.14

Roza, F. N. K. (2024). Security Convergence In Southeast Asia: Indonesia's Initiative In Asean Our Eyes (AOE) 2017. Ilomata International Journal of Social Science, Vol. 5 No. 3 (2024): July 2024, https-doi.

Schücking, M., Jochem, P., Fichtner, W., Wollersheim, O., & Stella, K. (2017). Charging Strategies for Economic Operations of Electric Vehicles in Commercial Applications. Transportation Research Part D Transport and Environment, 51, 173–189. https://doi.org/10.1016/j.trd.2016.11.032

Suguna, M., Shah, B., Raj, S., & Suresh, M. (2021). A Study on the Influential Factors of the Last Mile Delivery Projects During Covid-19 Era. Operations Management Research, 15(1–2), 399–412. https://doi.org/10.1007/s12063-021-00214-y

Song, L., Mao, B., Wu, Z., & Wang, J. (2019). Investigation of Home Delivery Models and Logistics Services in China. Transportation Research Record Journal of the Transportation Research Board, 2673(9), 11–22. https://doi.org/10.1177/0361198119844453

Streuling, C., Pagenkopf, J., Schenker, M., & Lakeit, K. (2021). Techno-economic assessment of battery electric trains and recharging infrastructure alternatives integrating adjacent renewable energy sources. Sustainability (Switzerland), 13(15). https://doi.org/10.3390/su13158234

Švadlenka, L., Bošković, S., Jovčić, S., Šimić, V., Kumar, S., & Zanne, M. (2023). Third-Party Logistics Provider Selection for Sustainable Last-Mile Delivery: A Case Study of E-Shop in Belgrade. Journal of Urban Development and Management, 2(1), 1–13. https://doi.org/10.56578/judm020101

Tritto, A., & Camba, A. (2023). The Belt and Road Initiative in Southeast Asia: A Mixed Methods Examination. Journal of Contemporary China, 32(141), 436–454. https://doi.org/10.1080/10670564.2022.2090099

Trippe, A., Arunachala, R., Massier, T., Jossen, A., & Hamacher, T. (2014). Charging Optimization of Battery Electric Vehicles Including Cycle Battery Aging. https://doi.org/10.1109/isgteurope.2014.7028735

Wang, X. (2023). The Impact of Logistics Development on Economic Growth for Shanxi Province in China: Empirical Evidence Based on System Dynamics. International Journal of Management and Economics Invention, 09(05). https://doi.org/10.47191/ijmei/v9i5.05

Xiang, Y., Meng, J., Huo, D., Xu, L., Mu, Y., Gu, C., Hou, K., & Teng, F. (2020). Reliability-oriented Optimal Planning of Charging Stations in Electricity–transportation Coupled Networks. Iet Renewable Power Generation, 14(18), 3690–3698. https://doi.org/10.1049/iet-rpg.2020.0005

Zhao, Y., Che, Y., Wang, D., Liu, H., Shi, K., & Yu, D. (2018). An Optimal Domestic Electric Vehicle Charging Strategy for Reducing Network Transmission Loss While Taking Seasonal Factors Into Consideration. Applied Sciences, 8(2), 191. https://doi.org/10.3390/app8020191

Zhang, X., Lin, Y., Wu, Y., & Skitmore, M. (2017). Industrial land price between China's Pearl River Delta and Southeast Asian regions: Competition or Coopetition? Land Use Policy, 61, 575–586. https://doi.org/10.1016/j.landusepol.2016.12.011

Zhou, S., Chen, B., Liu, H., Ji, X., Wei, C., Chang, W., & Xiao, Y. (2021). Travel Characteristics Analysis and Traffic Prediction Modeling Based on Online Car-Hailing Operational Data Sets. Entropy, 23(10), 1305. https://doi.org/10.3390/e23101305