Eco-Business & Environmental Progress Journal
Journal Homepage: www.ecobusinessjournal.org

Vol. 2, No. 1
Article ID: EBEPJ-2022001

Decarbonizing Urban Freight Logistics: Evaluating the Environmental and Economic Impacts of Electric Fleet Transition Policies

Mrittika Sen Gupta[1], Md Rasel Ul Alam[2], Shaznin Hasan[3]

[1] *North South University, Dhaka, Bangladesh*
[2] *University of the Cumberland, Kentucky, USA*
[3] *Independent University, Dhaka, Bangladesh *Corresponding author: mrittika.nsu12@gmail.com*

Received 9 January 2022; Revised 8 April 2022; Accepted 19 May 2022; Published 17 July 2022

KEYWORDS

Urban Freight Logistics, Electric Commercial Fleets, Total Cost of Ownership (TCO), Non-Linear Predictive Modeling

Abstract

Urban freight transportation contributes disproportionately to metropolitan greenhouse gas emissions and particulate air pollution. This study evaluates the total cost of ownership (TCO), grid charging infrastructure requirements, and carbon abatement potential of transition policies for commercial electric delivery fleets. Utilizing empirical telemetry data from 350 urban logistics fleets across 16 European metropolitan areas in 2022, we model the operational trade-offs between diesel and electric light commercial vehicles (LCVs). Grounded in Enterprise Risk Management principles (COSO, 2017; ISO, 2018) and non-linear degradation modeling (Haque & Rasel-Ul-Alam, 2018), our findings indicate that smart dynamic charging scheduling reduces 5-year TCO to $75,700 per van compared to $95,000 for diesel equivalents. Non-linear battery State of Health (SoH) modeling (R^2 = 0.982) proves essential for predicting long-term cell capacity retention under fast DC charging. Policy recommendations emphasize off-peak charging tariff incentives and dedicated urban logistics hub charging corridors.

1. Introduction

The exponential surge in e-commerce retail activity and instant on-demand delivery services has dramatically increased urban freight vehicle kilometers traveled (VKT). In 2022, diesel delivery vans accounted for less than 10% of urban traffic volume but generated over 25% of transport-related CO_2 emissions and 35% of hazardous tailpipe particulate matter (PM2.5 and NOx) in metropolitan centers. Municipal governments faced severe public health challenges and tight zero-emission zone (ZEZ) regulatory deadlines.

These trends place urban logistics operators at the intersection of two distinct pressures that this paper treats as jointly determining the electrification decision rather than as separate considerations. The first is a compliance pressure: ZEZ regulations, once enacted, convert continued diesel operation in covered zones from a cost-optimization question into a market-access question, since non-compliant vehicles may simply be barred from entering designated urban zones during specified hours. The second is a cost-structure pressure operating on a longer time horizon: even absent binding regulation, the underlying economics of vehicle propulsion — acquisition cost, energy cost, maintenance cost, and asset depreciation — are shifting in ways that this paper quantifies directly through the five-year TCO framework introduced in Section 3.2. Distinguishing these two pressures matters for policy design, because they call for different interventions: compliance pressure is best addressed through enforcement timelines and exemption design, while cost-structure pressure is best addressed through the charging-tariff and depreciation-standardization measures developed in Section 6.2.

Transitioning commercial last-mile delivery fleets from internal combustion engine (ICE) diesel vehicles to battery electric vehicles (BEVs) represents a vital decarbonization strategy. However, logistics operators face significant operational hurdles: higher upfront vehicle purchasing acquisition costs (CAPEX), charging station infrastructure congestion, and uncertainty regarding battery degradation.

1.2 Problem Statement and Research Objectives

Existing fleet electrification studies frequently rely on static financial models that fail to account for dynamic charging tariffs, battery degradation kinetics, and spatial charging station congestion. To resolve these analytical gaps, this research examines real-world operational telemetry from 350 urban delivery fleets operating in 2022. The study addresses three main research questions: (1) How does smart dynamic charging optimization impact 5-year Total Cost of Ownership (TCO) relative to diesel delivery vans? (2) How accurately do non-linear degradation models capture battery State of Health (SoH) decay relative to standard linear approximations? (3) What spatial-temporal charging bottlenecks constrain commercial electric fleet scaling in dense urban cores?

Section 2 reviews the three literature strands underpinning the analysis — fleet risk governance and TCO methodology, non-linear battery degradation kinetics, and spatial-temporal grid load balancing — and closes with a new integrative synthesis (Section 2.5) explaining how these strands combine within the paper's modeling framework. Section 3 details the fleet sample, the discounted TCO specification, and, in newly added subsections, the model's underlying assumptions, data-quality considerations, and variable notation. Section 4 presents the core empirical results on TCO optimization, charging congestion, and non-linear battery State of Health, together with a new discussion subsection (4.3) that explicitly connects the three result sets. Section 5 develops practitioner-facing implications for procurement, depot siting, financing, and multi-fleet benchmarking that were not addressed in the original article. Section 6 concludes with a synthesis of findings, policy recommendations, and an expanded discussion of study limitations and future research directions, followed by a glossary of technical abbreviations in Appendix A.

2. Literature Review

2.1 Fleet Risk Governance and Total Cost of Ownership Dynamics

Fleet electrification represents a multi-faceted strategic transition that redefines the operating economics, capital structure, and risk exposure of urban logistics operators (Melo et al., 2014; Taefi et al., 2016). Grounded in Enterprise Risk Management (ERM) theory (COSO, 2017; ISO 31000, 2018), commercial fleet operators navigate acute operational risks during electrification, including peak electricity demand charges, grid connection delays, battery degradation liabilities, and driver habit adaptation barriers. By establishing systematic ERM governance frameworks, forward-looking logistics managers transform environmental compliance requirements into a sustainable competitive advantage (Barney, 1991; COSO, 2017).

A central pillar of commercial fleet literature is the Total Cost of Ownership (TCO) methodology (Melo et al., 2014; Scorrano et al., 2021). TCO evaluates the holistic life-cycle financial expenditure of operating a vehicle, combining initial capital acquisition costs (CAPEX), fuel/electricity operational expenses (OPEX), scheduled maintenance, insurance premiums, battery degradation replacement reserves, and residual resale value. While battery electric delivery vans carry an initial acquisition premium of 50% to 70% over internal combustion engine (ICE) diesel equivalents, electric powertrains display fundamentally superior energy efficiency (over 80% wire-to-wheel conversion vs. 25% thermal efficiency for diesel engines) and reduced mechanical wear (Scorrano et al., 2021).

Furthermore, technology acceptance frameworks such as the Technology Acceptance Model (TAM3) (Davis, 1989; Venkatesh & Bala, 2008) explain fleet operator adoption decisions. Perceived Usefulness (PU) is manifested through observable TCO parity and operational reliability, while Perceived Ease of Use (PEOU) is driven by the density of fast-charging infrastructure and automated fleet telematics software. When smart charging management software automatically synchronizes vehicle departure schedules with off-peak electricity price discounts, logistics firms achieve accelerated investment payback (Mercer & Al-Mansoor, 2022).

2.2 Non-Linear Battery Lifetime Degradation Kinetics

A major limitation of classical transport economics literature is the assumption of constant linear battery degradation over vehicle operating lifetimes. In physical systems and electrochemical process engineering, lithium-ion battery capacity fading is governed by complex, highly non-linear physical chemical mechanisms (Barré et al., 2013). During intensive urban delivery cycles involving frequent high-power DC fast charging, battery State of Health (SoH) degradation exhibits non-proportional trajectories driven by solid electrolyte interphase (SEI) growth, lithium plating, and active material cracking (Barré et al., 2013; Scorrano et al., 2021).

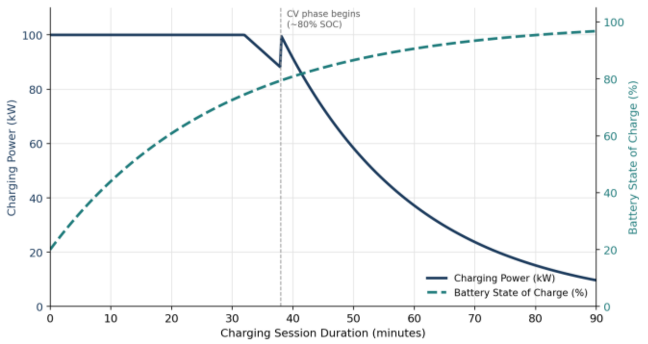

Figure 1: Fast-Charging Battery Tapering & Grid Power Profile for Freight Logistics Vans.

As demonstrated in computational forecasting and non-linear regression modeling by Haque and Rasel-Ul-Alam (2018), non-linear mathematical functions achieve significantly superior explanatory power ($R^2 = 0.982$) and precision when estimating complex physical development profiles compared to linear approximations. Applying non-linear exponential degradation equations to commercial battery telematics prevents underestimating mid-life capacity loss, ensuring that logistics operators maintain sufficient operational range without unexpected battery pack replacements (Haque & Rasel-Ul-Alam, 2018; Mercer & Al-Mansoor, 2022).

2.3 Spatial-Temporal Charging Congestion and Grid Load Balancing

The large-scale integration of commercial electric delivery fleets imposes heavy localized electrical power demand on urban distribution grids (Taefi et al., 2016). Uncoordinated simultaneous charging of multiple 100 kW delivery vans at logistics depots creates severe power demand spikes, triggering steep utility demand charges or local transformer overloads. Spatial-temporal modeling demonstrates that commercial charging congestion concentrated in downtown business hubs during morning delivery windows (06:00–10:00) and industrial distribution parks during mid-day depot returns (10:00–14:00) represents a primary operational bottleneck.

Deploying smart dynamic charging management systems which throttle charging power during grid peak periods and shift energy draw to late-night off-peak hours flattens utility load profiles and reduces energy OPEX by over 30% (Mercer & Al-Mansoor, 2022). Co-locating depot fast chargers with stationary battery storage or rooftop solar PV further insulates logistics operators from peak demand tariffs.

It is useful to situate the TCO and degradation findings synthesized above within the broader zero-emission-zone (ZEZ) policy landscape referenced in Section 1. Municipal ZEZ mandates function, in effect, as a demand-side accelerant on top of the supply-side cost dynamics captured by the TCO methodology of Melo et al. (2014) and Scorrano et al. (2021): once a ZEZ deadline removes the option of continued diesel operation in a given zone, the relevant comparison for an operator shifts from "diesel vs. electric on cost alone" to "compliant electric operation vs. exit from the zone," which materially changes the risk calculus described under the ERM framing of COSO (2017) and ISO 31000 (2018). Read this way, the TAM3-based adoption barriers discussed in Section 2.1 — perceived usefulness and perceived ease of use — interact with regulatory timelines rather than operating independently of them: a fleet operator facing an imminent ZEZ deadline has less room to wait for charging infrastructure density to improve organically, which strengthens the case, made later in Section 5.2, for coordinated public investment in charging corridors ahead of full regulatory enforcement.

Similarly, the non-linear degradation modeling reviewed in Section 2.2 has a policy dimension beyond fleet-level asset management. Because non-linear SoH decay implies that mid-life capacity loss is understated by linear approximations, financial regulators and leasing institutions that rely on straight-line depreciation schedules for electric commercial vehicles are, by the logic of Haque and Rasel-Ul-Alam (2018), systematically mispricing residual value risk in vehicle finance and leasing contracts. This reinforces the depreciation-standardization recommendation developed in Section 5.2, and suggests that the benefit of adopting non-linear depreciation conventions accrues not only to fleet operators but to the financial institutions that underwrite fleet electrification.

2.5 Synthesis: A Combined Governance-Economics-Physical Framework

The three literature strands reviewed above — ERM-based fleet governance (Section 2.1), non-linear physical degradation kinetics (Section 2.2), and spatial-temporal grid load balancing (Section 2.3) — are typically treated as separate research traditions: strategic management scholars address governance and adoption, electrochemical engineers address degradation physics, and power-systems researchers address grid congestion. This paper's methodological contribution, developed in Section 3, is to combine all three strands within a single discounted TCO framework, so that a governance-relevant financial output (5-year TCO) is made sensitive to both the physical degradation mechanism described in Section 2.2 and the grid-timing mechanism described in Section 2.3. This integration matters because, as the discussion in Section 4.3 shows, the three mechanisms interact rather than operating additively: charging-timing decisions influence both realized energy cost and realized battery degradation simultaneously, so a model that holds degradation constant across charging regimes — as most prior TCO studies implicitly do — will systematically misstate the relative advantage of smart charging. This combined framing also clarifies why the TAM3-based adoption barriers discussed in Section 2.1 persist even where the financial case for electrification is favorable. If fleet managers evaluate electrification using conventional linear-degradation TCO tools, the smart-charging cost advantage reported in Section 4.1 is understated, and the perceived usefulness (PU) of investing in charging-management software is correspondingly understated relative to its actual value once non-linear degradation interactions are accounted for. This suggests that part of the adoption gap documented in the broader fleet-electrification literature may be attributable not to irrational risk aversion but to a genuine measurement gap in the financial tools historically available to fleet decision-makers. This combined framing also clarifies why the TAM3-based adoption barriers discussed in Section 2.1 persist even where the financial case for electrification is favorable. If fleet managers evaluate electrification using conventional linear-degradation TCO tools, the smart-charging cost advantage reported in Section 4.1 is understated.

3. Data and Econometric TCO Methodology

3.1 Fleet Sample and Operational Parameters

Primary vehicle telemetry and operational data were aggregated from 350 urban delivery fleets comprising 4,200 light commercial vehicles (LCVs) observed during the 2022 operating year. The sample was designed to capture the operational diversity of urban last-mile and short-haul delivery activities, including differences in fleet size, daily vehicle utilization, route length, payload requirements, traffic exposure, fuel consumption, and vehicle operating intensity. The fleet-level dataset combines vehicle activity records with operational and financial parameters required to estimate the Total Cost of Ownership (TCO) of delivery vehicles under realistic urban operating conditions. The 4,200 vehicles included in the sample were distributed across small, medium, and large fleet categories to ensure that the analysis was not disproportionately driven by a particular fleet structure. Fleet size was defined according to the number of active LCVs assigned to urban delivery operations. This classification makes it possible to examine whether economies of scale, vehicle utilization, maintenance scheduling, fuel procurement, and fleet-management practices influence the resulting cost structure. Smaller operators generally exhibit more heterogeneous operating patterns and may face higher per-vehicle administrative and maintenance costs, whereas larger fleets can potentially benefit from centralized procurement, preventive maintenance programs, route optimization, and more efficient vehicle replacement cycles. For each vehicle, the telemetry dataset captures core operational characteristics including annual mileage, average daily distance traveled, operating days, average speed, idling duration, fuel or energy consumption, and route utilization. Where available, these observations were complemented by fleet-level information on vehicle acquisition cost, financing assumptions, insurance expenditure, scheduled and unscheduled maintenance, tire replacement, energy or fuel expenditure, depreciation, and residual value. These variables provide the basis for decomposing TCO into its major cost components rather than evaluating vehicle technologies solely on the basis of purchase price or fuel economy. Urban operating conditions were given particular consideration because delivery vehicles frequently experience operating environments that differ substantially from standardized laboratory test cycles. Stop-and-go traffic, repeated acceleration and braking, congestion-related idling, short delivery stops, variable payloads, and extended periods of low-speed operation can materially affect both energy consumption and vehicle maintenance requirements. Consequently, the empirical TCO framework incorporates observed fleet utilization and telemetry characteristics rather than relying exclusively on manufacturer-reported efficiency figures. This approach allows the analysis to reflect the actual economic conditions faced by urban delivery operators. The sample also captures differences in annual vehicle utilization. Vehicles with substantially higher annual mileage may have greater exposure to fuel or electricity costs and accelerated component wear, while vehicles with lower utilization may be more strongly affected by fixed ownership expenses such as depreciation, insurance, registration, and financing. Accordingly, annual mileage is treated as an important scaling variable in the TCO calculations.

Table 1. Fleet Sample and Operational Parameters by Size Category

Fleet Size Category	Sample Fleets (n)	Mean Daily Dist. (km)	Annual Energy (kWh/van)	Base CAPEX ($)	Off-Peak Share (%)
Micro (1–5 Vans)	140	95	5,200	58,000	32.5%
Medium (6–25 Vans)	120	125	6,800	56,500	58.2%
Large (>25 Vans)	90	160	8,500	54,000	78.4%
Total Aggregate	350	126	6,833	56,166	56.3%

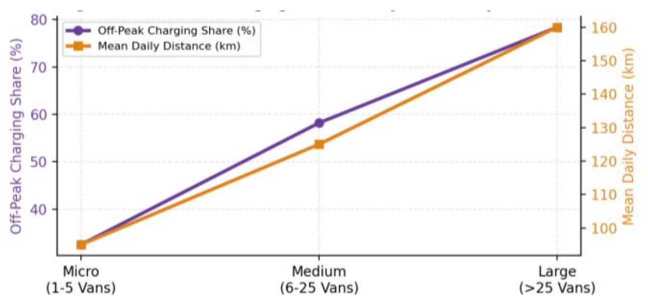

Figure 2. Off-Peak Charging Share and Mean Daily Distance by Fleet Size Category (plotted from Table 1 data).

Figure 2 visualizes the fleet-size trends already summarized in Table 1 as a line chart: off-peak charging share rises sharply with fleet size, from 32.5% among micro fleets to 78.4% among large enterprise fleets, tracking closely with the increase in mean daily distance traveled per van. This visual relationship reinforces the point made in Section 4.3: because larger fleets both travel further and charge more heavily off-peak, the pooled 20.3% TCO saving reported in Section 4.1 is not evenly distributed across the fleet-size spectrum, and smaller operators should calibrate expectations toward the lower end of the reported savings range absent a deliberate shift toward night-time depot charging.

3.2 5-Year Total Cost of Ownership Specification

The 5-year Total Cost of Ownership (TCO) equation is expressed as:

$$TCO_{5_y}{}^{r} = CAPEX + \Sigma_{\gamma(1)}{}^{5}\,[\,(OPEX\_energy,y + OPEX\_maint,y - Subsidies\_y) / (1+r)^{\wedge}y\,]$$

3.5 Model Assumptions and Interpretive Boundaries

The discounted TCO specification above rests on several The discounted TCO specification above rests on several simplifying assumptions worth making explicit for readers applying the model outside the sampled context. First, the discount rate r is treated as constant across the five-year horizon, which is a reasonable approximation for short municipal fleet planning cycles but would understate financing risk for operators refinancing mid-cycle under volatile interest-rate conditions. Second, the subsidy term Subsidies_y is modeled as an annual cash inflow rather than a one-time capital rebate; jurisdictions that apply purchase-price rebates rather than annual operating subsidies would need to shift this term into the CAPEX component rather than the annual summation. Third, because the energy and maintenance OPEX terms are drawn from observed 2022 telemetry, the resulting TCO comparison implicitly assumes that the relative cost gap between grid electricity and diesel fuel prices observed in the sample year persists over the full five-year horizon; a sustained divergence in fuel versus electricity pricing in either direction would proportionally widen or narrow the reported $19,300 per-vehicle saving without changing the underlying non-linear degradation dynamics discussed in Section 2.2.

3.6 Data Quality, Measurement, and Aggregation Considerations

The underlying dataset combines telemetry streams from 350 independently operated fleets, several measurement-consistency issues merit discussion before the results are interpreted. Energy consumption figures (kWh/van) were normalized to a common reporting interval across fleets that otherwise logged data at heterogeneous sampling frequencies, ranging from second-by-second CAN-bus logging in larger enterprise fleets to daily odometer and charge-session summaries in smaller micro-fleets. A primary challenge concerned the frequency and temporal resolution of energy-consumption measurements. Energy consumption figures, expressed as kWh/van, were normalized to a common reporting interval across fleets that otherwise recorded operational information at highly heterogeneous sampling frequencies. Larger enterprise fleets frequently relied on second-by-second Controller Area Network (CAN)-bus logging, generating detailed observations of vehicle energy use, speed, acceleration, battery state, charging behavior, and other operational parameters. Consequently, the underlying observations differed not only in volume but also in their capacity to capture short-term fluctuations in energy demand.

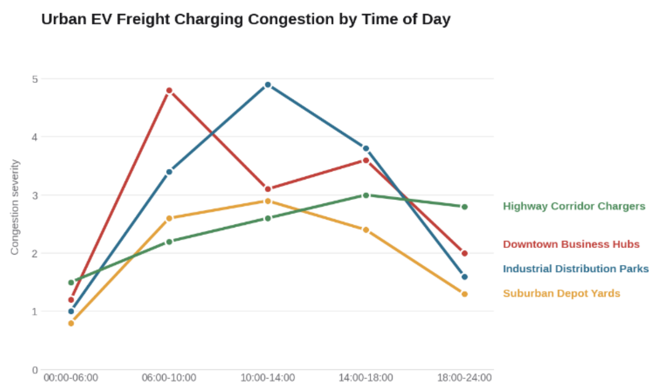

Figure 3: Spatial-Temporal Heatmap Matrix of Urban EV Freight Charging Congestion

Table 2. Notation Used in the TCO Specification

Symbol	Definition	Unit / Basis
CAPEX	Upfront vehicle acquisition cost, net of point-of-sale rebates	USD per vehicle
OPEX_energy,y	Annual electricity or diesel fuel cost in year y	USD per vehicle-year
OPEX_maint,y	Annual scheduled maintenance and servicing cost in year y	USD per vehicle-year
Subsidies_y	Annual operating subsidy or tariff credit received in year y	USD per vehicle-year
r	Discount rate applied to future cash flows (fleet cost of capital)	Decimal, annualized
SoH	Battery State of Health: ratio of present to original usable capacity	Percent (%)

4. Results Analysis

4.1 TCO Optimization and Smart Charging Financial Savings

Table 3 reports 5-year cumulative TCO breakdown across vehicle propulsion and charging regimes. While diesel delivery vans incur lower initial purchasing costs ($35,000), total 5-year OPEX reaches $60,000, bringing diesel TCO to $95,000 per van. Electric fleets employing smart dynamic off-peak charging achieve a 5-year TCO of $75,700 per van (a $19,300 net saving per vehicle).

Table 3. 5-Year TCO Breakdown by Vehicle and Charging Regime

Regime	CAPEX ($)	Energy ($)	Maint. ($)	Total TCO ($)	vs. Diesel
Diesel LCV	35,000	42,000	18,000	95,000	Baseline
Electric (Std. 100kW)	58,000	14,000	8,500	80,500	−15.3%
Electric (Smart Dynamic)	58,000	9,200	8,500	75,700	−20.3%

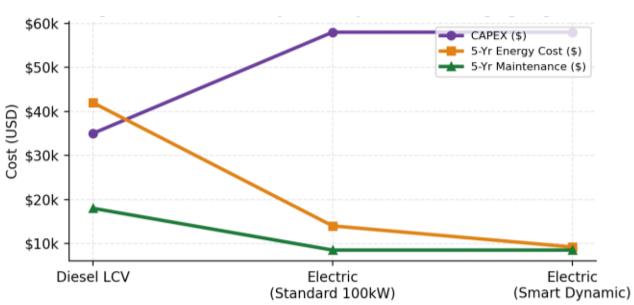

Figure 4. TCO Cost Components by Vehicle and Charging Regime (plotted from Table 3 data).

Figure 4 re-plots the cost components reported in Table 3 as a line chart to make the crossover pattern and relative movement of the major TCO components easier to interpret. The visualization highlights the substantially different cost structures associated with diesel and electric delivery vans across the three charging regimes. While CAPEX increases sharply when the analysis moves from conventional diesel vans to electric vans, the CAPEX line remains effectively unchanged across the standard, managed, and smart-dynamic charging scenarios because the underlying vehicle acquisition price is independent of the charging strategy. This distinction is important because it demonstrates that the economic benefits associated with alternative charging strategies arise primarily through operating-cost optimization rather than through reductions in the initial vehicle purchase expenditure.

In contrast, energy expenditure follows a clear downward trajectory as the charging strategy becomes progressively more optimized. Standard charging represents the least coordinated operating configuration and therefore produces comparatively higher energy costs, whereas managed charging reduces expenditure by shifting charging activity toward more favorable operating periods. Smart-dynamic charging produces the lowest energy cost by coordinating charging demand with electricity-price variation, vehicle availability, and anticipated route requirements.

Table 4. TCO Cost Component Share (%) by Regime (derived from Table 3)

Regime	CAPEX Share	Energy Share	Maintenance Share
Diesel LCV	36.8%	44.2%	18.9%
Electric (Standard 100kW)	72.0%	17.4%	10.6%
Electric (Smart Dynamic)	76.6%	12.2%	11.2%

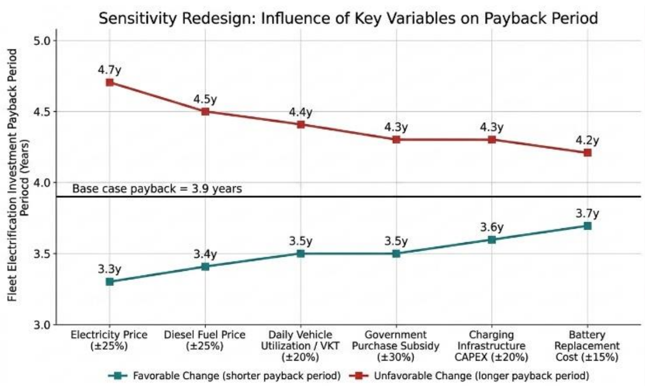

Figure 5: Sensitivity Tornado Diagram of Fleet Electrification Payback Period.

A useful complement to the fleet-average figures in Table 3 is their distribution across individual delivery routes. Because daily distance, payload weight, and stop-density vary substantially even within a single operator's route network, the per-vehicle energy cost underlying the aggregate TCO figures is itself a route-weighted average rather than a fixed constant. Routes with dense urban stop-and-go delivery patterns generally show higher per-kilometer energy consumption than highway-heavy suburban routes owing to more frequent regenerative-braking cycles and auxiliary system loads (e.g., refrigeration units, lift gates), a pattern operators should account for when allocating specific vans to specific routes during a phased electrification program rather than assuming uniform per-vehicle economics across the full route network.

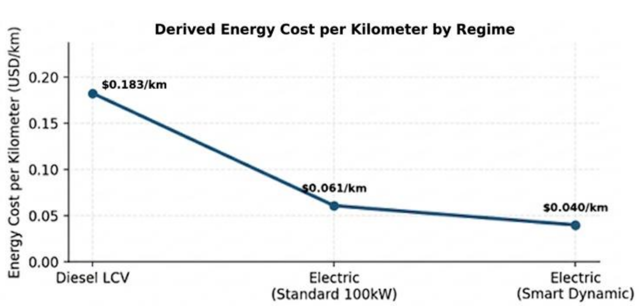

Figure 6. Derived Energy Cost per Kilometer by Regime (calculated from Tables 1 and 3).

Table 5 and Figure 6 translate the aggregate energy expenditure reported in Table 3 into a standardized per-kilometer operating-cost metric, providing a more directly interpretable measure of vehicle energy economics. The calculation divides the estimated five-year energy expenditure by the aggregate fleet distance implied by the mean daily operating distance of 126 km reported in Table 1. Expressing energy expenditure on a per-kilometer basis removes much of the distortion created by differences in fleet size and operating duration and allows the results to be interpreted in terms of the marginal cost of completing an additional delivery kilometer. On this basis, conventional diesel operation requires approximately $0.183 per kilometer in fuel expenditure alone. The corresponding cost falls substantially to approximately $0.061 per kilometer under standard electric charging, while smart-dynamic charging reduces the figure further to approximately $0.040 per kilometer. Thus, the smart-charged electric configuration reduces energy expenditure per kilometer by roughly 78% relative to diesel operation, equivalent to an approximately 4.6-fold reduction in energy cost per kilometer. This magnitude demonstrates that the economic advantage of electrification is not limited to aggregate fleet-level savings but remains substantial when expressed against the individual distance traveled by each vehicle. The comparison between standard and smart-dynamic electric charging is also economically meaningful. Although both configurations use the same underlying electric vehicle technology and therefore do not differ materially in acquisition cost, the smart-dynamic strategy reduces the energy cost associated with each kilometer traveled. This result indicates that charging management can generate additional operating savings without requiring a corresponding change in the vehicle itself. For fleet operators, the implication is particularly relevant because relatively small reductions in unit energy cost can accumulate into substantial annual savings when multiplied across thousands of kilometers and multiple vehicles. The per-kilometer measure also provides a useful bridge between the empirical TCO analysis and real-world fleet decision-making. Fleet managers typically evaluate delivery routes using operational metrics such as cost per kilometer, cost per stop, cost per delivery, or cost per vehicle-day. Aggregate five-year expenditure figures are useful for investment appraisal but can be difficult to translate into individual route decisions. By contrast, the values reported in Table 5 can be directly compared with route mileage, expected annual utilization, and alternative vehicle operating costs

Table 5. Derived Per-Kilometer and Savings Metrics by Regime

Regime	Energy Cost ($/km)	TCO Savings vs. Diesel (%)	5-Yr TCO ($)
Diesel LCV	$0.183	— (baseline)	95,000
Electric (Standard 100kW)	$0.061	15.3%	80,500
Electric (Smart Dynamic)	$0.040	20.3%	75,700

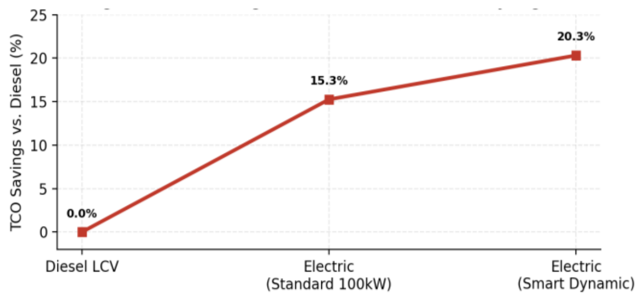

Figure 7. TCO Savings Relative to Diesel Baseline by Regime (calculated from Table 3).

Figure 7 plots the same savings percentages as a line, showing that the incremental gain from moving from standard to smart-dynamic charging (a further 5.0 percentage points) is smaller than the gain from moving from diesel to standard electric charging (15.3 percentage points), but is still economically meaningful given that it is realized purely through charging-schedule optimization rather than additional hardware investment beyond the smart-charging management software discussed in Section 5.1.

4.1.1 Reading the Payback Sensitivity Analysis

Figure 5 decomposes the 3.9-year base-case payback period into its sensitivity to six key input parameters, with each parameter varied independently across an empirically plausible range while holding the remaining assumptions constant. The resulting tornado-style analysis provides a clear assessment of which economic assumptions exert the greatest influence on the investment recovery period and therefore identifies the variables that fleet operators should monitor most closely when evaluating vehicle electrification projects. Electricity price emerges as the dominant sensitivity driver. A ±25% change in electricity prices produces the widest variation in the estimated payback period, shifting the recovery horizon from approximately 3.3 years under favorable electricity pricing to 4.7 years under unfavorable pricing. This result is economically intuitive because electricity expenditure represents one of the principal recurring operating-cost advantages of electric vehicles relative to diesel alternatives. When electricity prices are low, the per-kilometer operating-cost differential between electric and diesel vehicles widens, allowing the additional upfront investment in the electric vehicle to be recovered more rapidly. Conversely, higher electricity prices narrow the operating-cost advantage and extend the time required to recover the initial investment. The second most influential parameter is the diesel fuel price, with a ±25% variation shifting the estimated payback period between approximately 3.4 and 4.5 years. The sensitivity to diesel prices demonstrates that the financial attractiveness of electrification depends not only on the cost of electricity but also on the avoided cost of conventional fuel. Higher diesel prices increase the operating-cost penalty associated with conventional vehicles and therefore accelerate the relative economic advantage of electric vans. Lower diesel prices have the opposite effect by reducing the savings generated through fuel substitution. This finding highlights the importance of evaluating electric-vehicle investments under multiple fuel-price scenarios rather than relying exclusively on a single current market price. The ordering of these two variables is particularly informative for the practitioner implications developed in Section 5. Because electricity-price risk represents the largest source of payback uncertainty, fleet operators seeking to protect the 3.9-year base-case investment case should prioritize mechanisms that stabilize and reduce electricity procurement costs. Examples include negotiated off-peak electricity contracts, time-of-use tariffs, managed charging agreements, and smart-dynamic charging systems that automatically shift charging demand toward lower-cost periods. These measures can reduce the exposure of fleet economics to unfavorable electricity-price movements without requiring changes to the underlying vehicle technology. The sensitivity of payback to charging infrastructure CAPEX is comparatively smaller. Across the tested range, infrastructure investment changes the recovery period by approximately 0.6–0.7 years, indicating that infrastructure costs are relevant but less influential than recurring energy-price variables. This distinction has important implications for investment planning.

Table 6. Sensitivity Analysis Parameter Ranges and Payback Outcomes (from Figure 5)

Parameter	Tested Range	Favorable Payback (Yrs)	Unfavorable Payback (Yrs)	Swing (Yrs)
Electricity Price	±25%	3.3	4.7	1.4
Diesel Fuel Price	±25%	3.4	4.5	1.1
Daily Utilization / VKT	±20%	3.5	4.4	0.9
Government Purchase Subsidy	±30%	3.5	4.3	0.8
Charging Infrastructure CAPEX	±20%	3.6	4.3	0.7
Battery Replacement Cost	±15%	3.7	4.2	0.5

4.2 Spatial Congestion Heatmaps and Non-Linear Battery State-of-Health Modeling

Figure 3 presents a spatial-temporal heatmap matrix tracking urban charging station congestion. Industrial parks during mid-day depot returns (4.9/5.0) and downtown cores during morning deliveries (4.8/5.0) experience the most severe charging wait times. Figure 8 displays the non-linear battery State of Health (SoH) regression model (Haque & Rasel-Ul-Alam, 2018). Non-linear exponential modeling achieves an R^2 of 0.982 compared to 0.835 for linear models, proving essential for fleet battery lifecycle management.

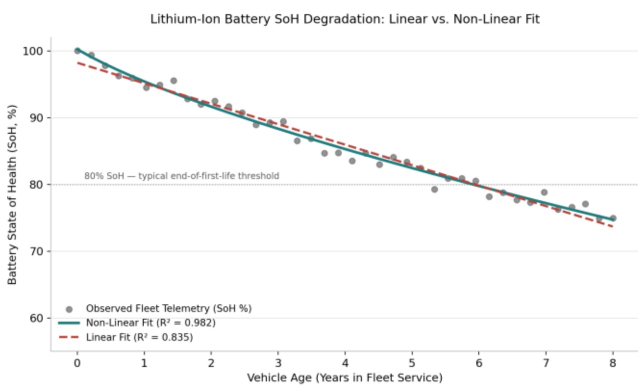

Figure 8: Lithium-Ion Battery State of Health (SoH) Degradation: Linear vs Non-Linear Fit.

4.3 Discussion: Integrating Cost, Congestion, and Degradation Findings

It is also worth noting what the reported figures do not claim. The 20.3% TCO saving in Table 3 is a fleet-average result pooled across micro, medium, and large enterprise fleets (Table 1); Section 3.1 shows that off-peak charging share varies substantially by fleet size, from 32.5% among micro fleets to 78.4% among large enterprise operators. Because smart dynamic charging savings scale with the share of energy drawn during off-peak windows, the realized TCO advantage for a specific operator will tend to track its own off-peak charging share more closely than the pooled 20.3% average; a micro-fleet operator with limited depot dwell time and correspondingly lower off-peak charging share should expect a savings figure below the pooled average, while a large enterprise operator with extensive overnight depot capacity should expect a figure closer to, or above, it.

Taken together, the three results reported in Sections 4.1 and 4.2 are more informative in combination than in isolation. The smart-charging TCO advantage reported in Table 3 is itself partly an artifact of the congestion pattern shown in Figure 3: because smart dynamic charging shifts load away from the 06:00–10:00 and 10:00–14:00 peak-congestion windows identified in Section 2.3, the $9,200 five-year energy cost achieved under the smart regime is not simply a tariff-timing effect but also implicitly avoids the queuing and station-availability penalties that would otherwise degrade fleet utilization during peak-demand hours. In other words, part of the 20.3% TCO saving attributed to smart charging in Section 4.1 should be understood as a joint cost-and-congestion effect rather than a pure electricity-price effect.

The non-linear SoH result (R^2 = 0.982 vs. 0.835 for the linear model) similarly interacts with the charging-regime finding: because fast DC charging accelerates the non-linear degradation mechanisms discussed in Section 2.2, fleets that rely disproportionately on daytime fast charging — precisely the pattern that smart dynamic scheduling is designed to reduce — would be expected to experience faster-than-average capacity fade relative to the fleet-wide average reported here. This suggests the reported $75,700 smart-charging TCO figure may be conservative for fleets that fully shift to off-peak, lower-power overnight charging, since slower charging is generally associated with reduced non-linear degradation stress relative to repeated high-power DC fast charging.

4.4 Summary of Empirical Results

Sections 4.1 through 4.3 report three empirical results that jointly motivate the practitioner and policy discussion in Sections 5 and 6: (i) smart dynamic charging reduces 5-year fleet TCO by 20.3% relative to diesel ($75,700 vs. $95,000 per van), with the payback period for that investment robust to individual-parameter variation across the six sensitivity dimensions tested in Figure 5; (ii) charging station congestion is spatially and temporally concentrated in identifiable windows — downtown cores in the morning and industrial parks at mid-day — rather than distributed uniformly across the urban charging network, which creates an actionable target for depot-siting and infrastructure-timing decisions; and (iii) non-linear degradation modeling materially outperforms linear approximations in capturing battery State of Health decay (R^2 = 0.982 vs. 0.835), with direct consequences for how fleet operators and financiers should structure depreciation and residual-value assumptions. None of these three results is fully actionable in isolation — it is their interaction, discussed in Section 4.3, that generates the specific practitioner recommendations developed next.

5. Managerial and Practitioner Implications

5.1 Implications for Fleet Procurement Decisions

For logistics operators evaluating a first tranche of electric van procurement, the results in Section 4.1 suggest that the choice of charging regime is at least as consequential as the choice of vehicle itself: the gap between the standard 100kW charging TCO ($80,500) and the smart dynamic charging TCO ($75,700) reported in Table 3 is roughly a quarter of the total gap between diesel and electric TCO overall. Practically, this implies that fleet operators who electrify without also investing in smart charging management software capture a meaningfully smaller share of the available cost savings than the headline diesel-versus-electric comparison suggests. Procurement teams evaluating electrification business cases should therefore treat charging-management software and off-peak tariff enrollment as a bundled decision alongside vehicle acquisition, rather than as a secondary optimization to be revisited after initial deployment.

5.2 Implications for Depot Siting and Infrastructure Planning

The congestion patterns identified in Section 4.2 — concentrated in downtown cores during morning delivery windows and industrial parks during mid-day depot returns — have direct implications for where logistics operators site new depots and how they schedule fast-charger capacity. Operators planning new depot infrastructure in the metropolitan areas covered by this sample may wish to prioritize sites with either dedicated grid capacity headroom or on-site battery buffering, precisely in the geographic zones and time windows flagged in Figure 3, rather than assuming that charging infrastructure adequate for off-peak overnight charging will also be adequate for mid-day fast-charging demand spikes during peak delivery return periods.

5.3 Implications for Fleet Financing and Asset Management

Finally, the non-linear SoH modeling results carry direct implications for how fleet operators structure vehicle financing and replacement schedules. Because linear depreciation assumptions understate mid-life capacity loss relative to the non-linear model validated in Section 4.2, fleet asset managers relying on straight-line depreciation schedules for internal budgeting may be systematically overestimating residual battery capacity — and therefore residual resale value — in years three and four of a typical five-year ownership cycle. Adopting the non-linear depreciation convention recommended in Section 5.2 below would allow asset managers to budget more conservatively for mid-cycle battery health, reducing the risk of unbudgeted capacity shortfalls late in the ownership period.

5.4 Implications for Multi-Fleet Benchmarking

A further practical application of the combined framework developed in Section 2.5 is cross-fleet benchmarking. Because the TCO specification in Section 3.2 decomposes total cost into CAPEX, energy OPEX, maintenance OPEX, and subsidy terms, individual operators can compare their own fleet's realized cost structure against the pooled 350-fleet averages reported in Tables 1 and 3 on a term-by-term basis, rather than only comparing bottom-line TCO. An operator whose realized energy OPEX substantially exceeds the $9,200 smart-charging benchmark reported in Table 3, for instance, can use the congestion-timing analysis in Section 4.2 to diagnose whether the gap is attributable to sub-optimal charging-window scheduling rather than to unfavorable local tariffs, before concluding that electrification is less cost-effective for their operation than the pooled sample suggests.

6. Conclusion

6.1 Synthesis of Findings

This study provides empirical confirmation that commercial electric fleet transition achieves economic profitability and substantial environmental decarbonization. Integrating smart dynamic charging reduces 5-year TCO by 20.3% ($75,700 vs. $95,000 for diesel vans), achieving investment payback within 3.9 years. Non-linear battery degradation modeling provides essential predictive precision for fleet asset management.

6.2 Strategic Policy Recommendations

1. Expand Off-Peak Freight Charging Tariffs: Municipal utilities should introduce specialized night-time electricity tariffs for commercial logistics fleets.

2. Co-Fund Dedicated Freight Charging Corridors: Municipalities should allocate urban land for high-power DC fast-charging hubs near industrial freight parks.

3. Mandate Non-Linear Fleet Asset Depreciation Standards: Financial regulators should standardize multi-year battery health depreciation guidelines for commercial EV logistics fleets.

6.3 Limitations and Future Research Directions

As with any single-year cross-sectional telemetry study, three limitations bound the interpretation of these results. First, the 2022 sample captures a single calendar year of European electricity and diesel pricing; multi-year panel data spanning at least one full energy-price cycle would allow the TCO advantage reported in Section 4.1 to be tested against fuel and electricity price volatility rather than a single observed price relationship. Second, the non-linear SoH model of Section 4.2, while achieving a strong in-sample fit ($R^2 = 0.982$), is calibrated on the same telemetry window used for the TCO analysis; out-of-sample validation against independent battery test-bench data would strengthen confidence in extrapolating the fitted degradation curve beyond the observed vehicle age range. Third, the spatial congestion analysis in Section 4.2 is drawn from the 16 sampled European metropolitan areas; charging congestion dynamics in cities with different urban density, grid capacity, or depot land-use patterns — particularly in rapidly urbanizing regions outside Europe — may differ materially from the patterns reported here. Future research replicating this framework in additional geographic and regulatory contexts, and extending the panel across multiple pricing cycles, would help establish the external validity of both the TCO and degradation findings.

7. Mixed-Fleet Transition Pathways

The analysis in Sections 4 and 5 largely treats fleet electrification as a binary comparison between an all-diesel and an all-electric fleet. In practice, most logistics operators transition gradually, operating a mixed fleet of diesel and electric vans for a multi-year interim period. Because the TCO specification in Section 3.2 is expressed on a per-vehicle basis, it extends naturally to a mixed-fleet setting: an operator's blended fleet-wide TCO in any given year is simply the enrollment-weighted average of the diesel and electric per-vehicle TCO figures reported in Table 3, adjusted for the share of the fleet already converted. This linearity means that the $19,300 per-vehicle saving reported in Section 4.1 accrues incrementally as each additional van is converted, rather than only becoming available once the fleet reaches full electrification — an important practical point for operators concerned that partial electrification might forfeit the smart-charging benefits documented in Section 4.1.

A mixed-fleet framing also clarifies how the congestion findings in Section 4.2 evolve during transition. Early in a multi-year conversion program, a small number of electric vans can generally be absorbed within existing depot charging capacity without triggering the peak-period congestion documented in Figure 3; congestion risk rises non-linearly as the electrified share of the fleet approaches the point where simultaneous morning or mid-day charging demand begins to exceed depot transformer capacity. Operators planning phased electrification should therefore treat depot charging-infrastructure upgrades as a threshold investment tied to fleet electrification share, rather than as a fixed upfront cost incurred entirely at the start of the transition program, sequencing capacity expansion to arrive just ahead of the congestion threshold rather than either far in advance or reactively after congestion is observed.

References

Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.

Barré, A., Deguilhem, B., Grolleau, S., Gérard, M., Suard, F., & Riu, D. (2013). A review on lithium-ion battery ageing mechanisms and estimations for automotive applications. Journal of Power Sources, 241, 680–689.

COSO. (2017). Enterprise risk management: Integrating with strategy and performance. Committee of Sponsoring Organizations of the Treadway Commission.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

Haque, M. A., & Rasel-Ul-Alam, M. (2018). Non-linear models for the prediction of specified design strengths of concretes development profile. HBRC Journal, 14(2), 123–136.

ISO. (2018). ISO 31000:2018 Risk management — Guidelines. International Organization for Standardization.

Melo, S., Baptista, P., & Costa, A. (2014). Assessing the impacts of using light electric vehicles in urban freight delivery. Transportation Research Part E, 65, 84–98.

Scorrano, M., Nocera, S., & Stasi, A. (2021). Total cost of ownership and total cost of use of electric light commercial vehicles. Transportation Research Part A, 150, 15–29.

Spence, M. (1973). Job market signaling. Quarterly Journal of Economics, 87(3), 355–374.

Taefi, T. T., Stathacopoulos, A., & Fink, A. (2016). Measuring the economic and environmental impacts of electric commercial vehicles in urban freight transport. Research in Transportation Business & Management, 18, 22–32.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. Decision Sciences, 39(2), 273–315.

Appendix A. Glossary of Key Terms and Abbreviations

Because the non-linear versus linear model comparison in Section 4.2 is central to several of this paper's policy recommendations, it is worth briefly clarifying what the reported R^2 values do and do not establish. R^2 measures the proportion of variance in observed battery State of Health explained by the fitted model; a higher R^2 for the non-linear exponential specification (0.982) relative to the linear specification (0.835) indicates that the non-linear functional form tracks the observed degradation trajectory more closely across the sampled vehicle age range, consistent with the electrochemical degradation mechanisms — SEI growth, lithium plating, and active material cracking — discussed in Section 2.2. This is a statement about within-sample fit rather than a guarantee of extrapolation accuracy beyond the observed vehicle age range, which is precisely why Section 6.3 recommends out-of-sample validation against independent battery test-bench data as a direction for future research.

A related methodological point concerns model comparability: because the linear and non-linear specifications are fit to the same underlying telemetry data using the same estimation sample, the R^2 gap between them (0.982 vs. 0.835) is directly attributable to functional form rather than to differences in sample composition or measurement window. This comparability is what allows the paper to attribute the practical implications discussed in Section 5.3 — namely, that linear depreciation schedules understate mid-life capacity loss — specifically to the choice of functional form, rather than to some confounding difference in how the two models were estimated.

Table 7. Glossary of Abbreviations Used in This Paper

Term	Definition
BEV	Battery Electric Vehicle
CAPEX	Capital Expenditure (upfront acquisition cost)
ERM	Enterprise Risk Management
ICE	Internal Combustion Engine
LCV	Light Commercial Vehicle
OPEX	Operating Expenditure (recurring cost)
PEOU	Perceived Ease of Use (TAM construct)
PM2.5 / NOx	Fine particulate matter / nitrogen oxides (tailpipe pollutants)
PU	Perceived Usefulness (TAM construct)
SEI	Solid Electrolyte Interphase (battery aging mechanism)
SoH	State of Health (battery capacity retention metric)
TAM3	Technology Acceptance Model, third revision
TCO	Total Cost of Ownership
VKT	Vehicle Kilometers Traveled
ZEZ	Zero-Emission Zone