



Assessing the Electrification Potential of Heavy-Duty Road Freight in India: A Duty-Cycle and Well-to-Wheel Emissions Assessment

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Abstract

Battery-electric heavy-duty trucks are entering commercial service in India, but whether they reduce greenhouse-gas (GHG) emissions on a coal-intensive grid depends on how efficient they are relative to the diesel operations they replace. Existing Indian assessments rely largely on representative vehicle archetypes and simulated drive cycles. This study links operator-reported duty cycles of 92 diesel trucks (22 operators, northern India) with electric-truck specifications, one measured electric trip and a register of 58 electric-truck deployment records to estimate well-to-wheel (WTW) emissions, break-even conditions and operational feasibility by freight segment. Diesel WTW emissions ranged from 0.40 to 2.13 kg CO₂e/km across five segments, and 47.5-t construction tippers accounted for 71% of the sample's 11,128 t CO₂e per year. On the current national grid (0.727 kg CO₂/kWh), the modelled electric counterfactual reduced WTW emissions by 43% for tippers, 14% for medium trucks and 4% for 40–55-t trucks but increased them by 52–59% for 14–32-t rigid and box trucks whose diesel baselines are already efficient (6.5–7 km/L). The break-even electric-truck energy consumption, which is independent of annual distance, ranged from 0.50 to 2.64 kWh/km. Under the projected 2029–30 grid (0.477 kg CO₂/kWh), all segments except 28–32-t box trucks broke even or better, and solar charging yielded reductions of 91–97%. Feasibility was a separate constraint: only one 55-t model covered the median daily energy demand on a single charge, most cases required a mid-shift charge of 0.3–7.4 h, and payload was insufficient for tipper and medium-truck proxies. Screening of the deployment register suggested that about one-third of deployed trucks operate captive port, mine or in-plant duty cycles compatible with a single daily charge. The findings indicate that the GHG case for heavy-duty electrification in India is segment-specific and conditional on vehicle efficiency and grid decarbonization, and they provide a transparent break-even framework that can be updated as measured Indian electric-truck data become available.

Keywords: battery-electric trucks; heavy-duty freight; well-to-wheel emissions; break-even energy consumption; duty cycle; grid emission factor; India.

Introduction

1.1 Background

Road freight is one of the more difficult parts of the transport sector to decarbonize. Heavy trucks cover long daily distances, carry large and variable payloads and depend on the high energy density of diesel. In India, freight demand has grown steadily and is expected to keep growing over the coming decades, with road transport carrying the largest share of goods movement (NITI Aayog et al., 2021). Reducing the emissions of heavy trucks is therefore central to any credible decarbonization pathway for Indian freight.

1.2 Heavy-duty road freight and emissions

The annual emissions of a truck are the product of three quantities that vary widely between operations: distance travel, energy use per kilometer and the carbon intensity of the energy carrier. Payload and empty running then determine how those emissions translate into freight work. Because these quantities differ between applications, fleet-average or archetype-based assessments may conceal large differences between individual freight duty cycles.

1.3 Electrification of heavy-duty freight

Battery-electric trucks are now commercially deployed in India in gross vehicle weight (GVW) classes from about 7.5 t to 55 t. The deployment register compiled for this study lists 58 public records covering 1,903 trucks either operating or ordered, concentrated in 55-t tractor-trailers used in cement, port, mining and steel logistics. Lifecycle and cost studies suggest that battery-electric trucks can already offer lower emissions and competitive costs in India (International Council on Clean Transportation [ICCT], 2024a, 2024b; Rajagopal et al., 2024). International evidence, however, shows that the WTW advantage of electricity-dependent powertrains narrows or disappears where electricity is carbon-intensive (Gustafsson et al., 2021), and that the share of trucks that can be replaced one-for-one depends strongly on duty cycle (Zhao et al., 2024).

1.4 Indian freight context

India's national grid emission factor was 0.727 kg CO₂/kWh in 2023–24 (Central Electricity Authority [CEA], 2024), and the CEA projects a decline to 0.477 kg CO₂/kWh by 2029–30 (CEA, 2023). On a grid of this intensity, the emissions advantage of an electric truck is not automatic: it depends on the electricity it draws per kilometer relative to the diesel it displaces. Indian heavy-truck operations are also heterogeneous, ranging from short captive shuttles inside ports and mines to long inter-city corridors, with frequent overloading and variable empty running.

1.5 Research gap

Indian studies of heavy-duty truck electrification have characterized vehicles through representative archetypes (ICCT, 2024a), cost-of-ownership models (ICCT, 2024b; Rajagopal et al., 2024) or simulated drive cycles (Madichetty et al., 2022). Within the literature reviewed, there is limited evidence that links observed Indian diesel duty cycles to matched electric counterfactuals, WTW emissions, break-even thresholds and engineering feasibility within a single, reproducible framework. In particular, the conditions under which electrification does or does not reduce emissions in specific Indian freight segments have not been quantified in a form that can be updated as measured electric-truck data emerge.

1.6 Research questions

RQ1. What is the real-world energy-use characteristics and WTW GHG emissions of the observed heavy-duty diesel freight operations?

RQ2. How do battery-electric trucks compare with comparable diesel trucks in WTW energy use and GHG emissions?

RQ3. How does the WTW GHG benefit of electrification vary across freight segments, duty cycles, vehicle characteristics and grid scenarios?

RQ4. Which observed duty cycles are technically compatible with available electric trucks, given daily distance, energy demand, battery capacity, charging requirements and payload?

RQ5. Under what combinations of electric-truck energy consumption and grid emission intensity do electrification produce a WTW GHG advantage over diesel?

1.7 Contributions

The study makes three contributions. First, it provides an operator-level diesel WTW baseline for five Indian heavy-duty segments. Second, it derives segment-specific break-even electric-truck energy consumption and grid intensities that are independent of annual distance and of any single electric-truck model, and it tests their robustness. Third, it assesses technical feasibility as a set of explicit constraints (vehicle availability, single-charge energy, mid-shift charging and payload) rather than as a weighted score, and it compares the resulting picture with the observed pattern of electric-truck deployment. Costs, business models, operator adoption and fleet-transition planning are outside the scope of this paper.

2. Literature review

2.1 Real-world energy use of heavy-duty freight

Diesel fuel economy of heavy trucks depends on payload, gradient, speed, idling and body type. Indian evidence on in-use fuel economy is sparse and mostly based on surveys or type-approval data, and national assessments therefore tend to adopt representative values for a small number of vehicle classes (ICCT, 2024a; NITI Aayog et al., 2021). What remains uncertain is how widely in-use fuel economy varies between Indian freight applications. The present study addresses this with operator-reported fuel economy for five observed segments, treating the reported values as operator estimates rather than measurements.

2.2 Battery-electric heavy-duty truck energy consumption

Measured energy consumption of battery-electric trucks increases with vehicle mass and decreases with ambient temperature. In German regional delivery, trucks of up to 19 t averaged about 0.80 kWh/km, rising to about 1.14 kWh/km in the 34–40-t class under favorable conditions (Le Corguillé et al., 2025). Large operational datasets from China indicate that only a minority of electric delivery trucks and semi-trailers can currently replace diesel trucks one-for-one, because range and charging constraints bind in many duty cycles (Zhao et al., 2024). In India, published data are largely limited to manufacturers' rated range and battery capacity, and to simulation of medium-duty trucks on an Indian drive cycle (Madichetty et al., 2022). This study therefore uses a transparent evidence hierarchy for electric-truck energy consumption and tests the sensitivity of its conclusions to that parameter.

2.3 WTW and life cycle GHG assessment

WTW assessments combine upstream fuel or electricity emissions with vehicle-use emissions. Their outcome is highly sensitive to grid carbon intensity: Gustafsson et al. (2021) show that energy carriers with high electricity dependence are not necessarily better than diesel on a WTW basis when the grid is carbon intensive. For India, ICCT (2024a) estimates that battery-electric heavy-duty vehicles charged with renewable electricity have 78–83% lower life-cycle emissions than diesel, with smaller reductions on the current grid. Such studies usually report results for representative vehicles; they rarely express results as thresholds that can be compared directly with the efficiency of specific electric models or with specific diesel duty cycles. The break-even formulation used here addresses this limitation.

2.4 Duty-cycle, range and charging feasibility

Feasibility studies commonly compare daily energy demand with usable battery energy and, where needed, the energy that can be replenished during scheduled stops. Commodity-level analysis in Finland and Switzerland found that the electrifiable share of tonne-kilometres differs markedly between countries and commodities, largely because of vehicle size and trip length (Liimatainen et al., 2019). Composite readiness indices are common but often rely on weights that are difficult to justify. This study instead reports each constraint separately and derives a categorical classification from explicit rules.

2.5 Indian freight electrification evidence

Indian studies have focused on cost parity (ICCT, 2024b; Rajagopal et al., 2024), national emissions scenarios (NITI Aayog et al., 2021) and representative life-cycle comparisons (ICCT, 2024a). These studies indicate that electrification can lower costs and emissions for some segments, but they do not examine how the result changes

across observed Indian duty cycles or under which electric-truck efficiency the advantage disappears.

2.6 Research gap and analytical positioning

Table 1. Literature evidence matrix.

Study	Geography	Vehicles	Data basis	Real-world operations	WTW / LCA	Duty cycle	Limitation for this study
ICCT (2024a)	India	12-t rigid, 55-t tractor, bus	Archetypes	No	LCA	No	No observed duty cycles
ICCT (2024b)	India	Heavy trucks	Archetypes	No	No	No	Cost focus
Rajagopal et al. (2024)	India	Four truck classes	Modelled	No	Partly	Partly	Cost focus
Madichetty et al. (2022)	India	Medium-duty	Simulated drive cycle	No	No	Yes	No emissions or feasibility
Gustafsson et al. (2021)	Sweden/Europe	Heavy trucks	Modelled	No	WTW	No	Not Indian grid
Liimatainen et al. (2019)	Finland, Switzerland	Heavy trucks	Commodity trip data	Partly	No	Yes	No WTW; not India
Zhao et al. (2024)	China	Delivery trucks, semi-trailers	Operational big data	Yes	Life cycle	Yes	Not India
Le Corguillé et al. (2025)	Germany	11–40-t trucks	Measured	Yes	No	Partly	European conditions

Note. LCA = life-cycle assessment; WTW = well-to-wheel.

Within the studies reviewed, none combines observed Indian diesel duty cycles, matched electric counterfactuals, WTW break-even thresholds and constraint-based feasibility. This combination defines the analytical position of the present study. The claim is limited to the literature identified and is not a statement that no such study exists.

3. Data and methods

3.1 Analytical framework and study design

The study follows the chain shown in Figure 1: observed diesel operations provide an energy and WTW baseline; matched electric counterfactuals provide the corresponding electricity demand and WTW emissions; the two are compared directly and through break-even thresholds; and duty-cycle constraints determine whether the counterfactual is operationally feasible. All calculations were implemented in a formula-driven spreadsheet model in which raw data, user-confirmed corrections, parameters, calculations and outputs are held in separate layers, and headline results were reproduced independently in a scripted recalculation.

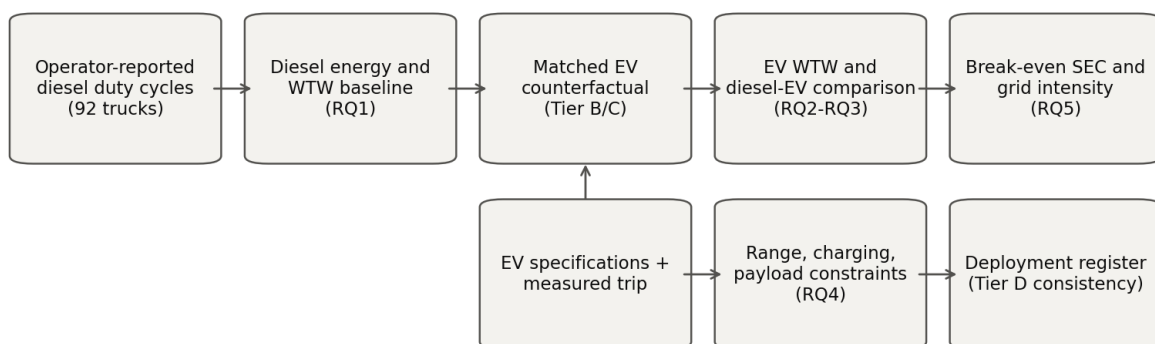


Figure 1. Analytical framework (original conceptual schematic).

3.2 Diesel vehicle dataset

The diesel dataset was collected through a field survey of truck operators registered in Delhi, Haryana, Uttar Pradesh, Punjab and Maharashtra. For each truck, operators reported the manufacturer and model, GVW, maximum payload, model year, emission standard, body type, fuel, average load, empty-running share, fuel economy at average, full and empty load, and monthly distance. The survey covered 104 trucks. Values were

frequently reported as fleet averages and repeated across trucks of the same operator.

3.3 Electric-truck technical and deployment evidence

Electric-truck technical data were compiled from manufacturers' published specifications (gross battery capacity, rated range, payload and charging power where published) and from one measured trip of an 18.5-t electric rigid truck (1,024 kWh over 1,192 km). A separate register of 58 electric-truck deployment records was compiled from company announcements, press reports and professional-network posts. The register records customer, industry, manufacturer, application, corridor, GVW and the number of trucks operating or ordered. It is used only as deployment evidence (Tier D in Section 3.9) and not as evidence of energy performance.

3.4 Data cleaning and validation

Raw survey values were preserved unchanged; corrections confirmed by the data owner were applied from a separate edit layer, and all validation rules were implemented as formulas. Eight user-confirmed corrections were applied (for example, a model year recorded as "4" corrected to 2022, and a monthly distance of 60,000 km corrected to 10,000 km). A truck was excluded when a core field was missing, when payload was equal to or greater than GVW, when average load exceeded GVW, or when monthly distance exceeded 50,000 km. One truck was excluded because its reported average load (10 t) exceeded its GVW (4 t); eleven CNG trucks were set aside because the analysis concerns diesel baselines. The resulting analytical sample contains 92 diesel trucks from 22 operators, forming 28 operator–segment clusters. Three trucks with full-load fuel economy reported as higher than average-load fuel economy were retained and flagged. Empty running values recorded per 1,000 (for example, "200/1000") were converted to fractions. The source spreadsheet's annual-fuel column, which multiplied distance by fuel economy, was not used.

Trucks were grouped into five segments by body type and GVW: S1 box rigid trucks of 28–32 t (inter-warehouse parcel freight); S2 rigid trucks of 14–20 t (chemicals, plywood and general cargo); S3 tippers of 47.5 t (construction material for highway projects); S4 heavy open trucks of 40–55 t (bulk loads); and S5 medium trucks below 14 t. The GVW thresholds follow the observed clustering of the sample and are not a national classification.

3.5 Variable definitions

Table 3. Variable definitions and provenance.

Variable	Definition	Unit	Provenance
GVW	Empty weight plus payload, as reported	t	Reported
Average load, L	Load carried on loaded trips (interpretation; see Section 3.10)	t	Reported
Empty share, ε	Share of distance travelled empty	fraction	Reported, unit-corrected
Fuel economy, η	Fuel economy at average load	km/L	Reported
Annual distance, D	Monthly distance $\times$ 12	km/yr	Derived
Daily distance, d	Monthly distance $\div$ operating days (26 per month)	km/day	Derived (assumed days)
Specific energy consumption, sEV	Battery-side electricity per km	kWh/km	Measured or derived from manufacturer data
Grid factor, EFgrid	Emissions per kWh generated	kg CO ₂ /kWh	External (CEA)

3.6 Diesel energy consumption

Annual diesel consumption F (L/yr), energy per kilometer ed (MJ/km) and annual energy Ed (MJ/yr) were calculated for each truck as

$$F = D / \eta, \quad ed = \rho \cdot NCV / \eta, \quad Ed = F \cdot \rho \cdot NCV \quad (1)$$

where ρ is diesel density (0.832 kg/L) and NCV is net calorific value (43.0 MJ/kg; Eggleston et al., 2006).

3.7 EV energy consumption

Electricity drawn from the grid for the same annual distance was calculated as

$$EEV = D \cdot sEV / [\eta_{ch} \cdot (1 - \lambda_{TD})] \quad (2)$$

where η_{ch} is charging efficiency (0.90) and λ_{TD} is a transmission-and-distribution loss term. Because the grid factor used here is a national generation-based average and no upstream electricity term is added, λ_{TD} was set to zero to avoid double counting; this choice is examined in the Discussion. Specific energy consumption followed an evidence hierarchy: measured values where available (the 18.5-t measured trip, 0.859 kWh/km); otherwise, values derived from manufacturer data as usable battery energy divided by the mid-point of rated range, with usable energy assumed to be 80% of gross capacity.

3.8 Well-to-wheel emissions

WTW emissions for diesel (Gd) and electric operation (GEV) were calculated as

$$Gd = F \cdot EF_{WTW}, \quad GEV = EEV \cdot EF_{grid}, \quad R = (Gd - GEV) / Gd \quad (3)$$

with a diesel WTW factor EF_{WTW} of 3.2 kg CO₂e/L (Smart Freight Centre, 2023). The combustion (tank-to-wheel) component, 2.65 kg CO₂/L, follows from the IPCC default carbon content of gas/diesel oil (74.1 kg

CO₂/GJ; Eggleston et al., 2006) and the density and NCV above. Three electricity scenarios were used: the current national grid (0.727 kg CO₂/kWh; CEA, 2024), the CEA projection for 2029–30 (0.477 kg CO₂/kWh; CEA, 2023) and solar charging (0.041 kg CO_{2e}/kWh, a life-cycle median for rooftop photovoltaics; Schlömer et al., 2014). The system boundary covers fuel production and distribution, electricity generation, charging losses and vehicle operation. Vehicle, battery and infrastructure manufacturing and end-of-life are excluded; the analysis is therefore a WTW assessment and not a full life-cycle assessment.

3.9 Diesel–EV matching methodology

Each diesel segment was matched to the electric truck of the same GVW class and freight function where one exists. Where none exists, specific energy consumption was interpolated linearly in GVW between the measured 18.5-t truck and the mean of three distinct 55-t models (1.176 kWh/km). For tippers, the interpolated value was multiplied by an assumed duty-cycle factor of 1.35 to reflect site operation and haulage on gradients; the factor varied between 1.0 and 2.15 in sensitivity analysis, the upper bound being the observed ratio of diesel fuel use per km between tippers and heavy open trucks. Evidence was classified into four tiers: A, observed paired operation; B, matched operational evidence; C, modelled proxy; and D, deployment evidence only. No Tier A comparison was possible because the diesel sample contains no cement, port or mining operations. Segments S2 and S4 are Tier B; S1, S3 and S5 are Tier C (Table 6). The comparison is made per kilometer over the same annual distance, which assumes that the electric truck performs the same route; payload differences are treated separately as a feasibility constraint.

3.10 Tonne-km and freight-efficiency metrics

Freight work was calculated as

$$TK = D \cdot (1 - \varepsilon) \cdot L \quad (4)$$

which is valid if L refers to the load carried on loaded trips. If the reported average load already averages over empty trips, the factor (1 – ε) double-counts empty running. Because the questionnaire wording does not resolve this, intensities are reported under both readings.

3.11 Duty-cycle modelling

Daily distance was calculated as monthly distance divided by 26 operating days, and daily energy demand as $Q = d \cdot sEV$. For the deployment register, one-way corridor distances were taken as approximate road distances for named city pairs or, where the corridor was internal or unrecorded, as archetype defaults (port or mine, 10 km; inside plant, 5 km; urban, 30 km; unrecorded regional, 150 km). Round trips per day were estimated as a 16-hour operating day divided by the round-trip driving time plus a turnaround allowance (0.5–3 h by archetype). These corridor values are assumptions and are used only as a screening of deployed duty cycles.

3.12 Range feasibility

A duty cycle was classified as single-charge feasible if

$$Q \leq Buse \cdot (1 - r) \quad (5)$$

where Buse is usable battery energy and r an additional operating reserve, set to zero because the 80% usable window already provides a state-of-charge buffer. A continuous feasibility margin, $M = [Buse(1 - r) - Q] / Q$, was also calculated. Temperature, terrain, auxiliary loads and battery degradation were not modelled.

3.13 Charging feasibility

Where single-charge operation was infeasible, the mid-shift charging time required was calculated as

$$tch = \max(0, Q - Buse) / (Pch \cdot \eta_{ch}) \quad (6)$$

using published charging power where available. Because operator dwell times were not available, the result is reported as the dwell time required rather than as a pass or fail. Where charging power was not published, the charging time is reported as not estimable. For the 18.5-t truck, a charging power of 60 kW was assumed.

3.14 Payload feasibility

Payload feasibility was expressed as the ratio of the electric truck's rated payload to the segment median average load. A ratio of at least 1.0 passes, 0.9–1.0 is conditional and below 0.9 fails; these thresholds are engineering interpretations. For the tipper proxy, electric payload was estimated as the diesel tipper payload (30 t) minus battery mass at 6 kg/kWh of gross capacity.

3.15 Readiness classification

Readiness was derived from explicit constraints rather than weights. A case is low if a vehicle of the required class is unavailable, if payload fails, or if required charging is infeasible; high if daily energy fits on a single charge and payload passes; and conditional otherwise, typically where a mid-shift charge is required. The classification is reported alongside the underlying constraints so that it can be re-evaluated if any input changes.

3.16 Break-even analysis

Setting $GEV = Gd$ for the same distance and solving gives the break-even specific energy consumption and grid intensity

$$sEV^* = gd \cdot \eta_{ch} \cdot (1 - \lambda TD) / EF_{grid}, \quad EF_{grid}^* = gd \cdot \eta_{ch} \cdot (1 - \lambda TD) / sEV \quad (7)$$

where $gd = EF_{WTW} / \eta$ is diesel WTW emissions per kilometer (kg CO_{2e}/km). The units reduce to kWh/km and kg CO₂/kWh respectively. An electric truck with $sEV < sEV^*$ emits less than the diesel truck it replaces. Because both emissions terms are linear in distance, annual distance cancels: utilization changes the tonnes of CO_{2e} avoided each year but not whether electrification reduces emissions.

3.17 Sensitivity analysis

Each key input (diesel fuel economy, grid factor, diesel WTW factor, charging efficiency and electric-truck energy consumption) varied by 20%. Because empirical ranges are not available for most inputs, this is an analytical stress test rather than a confidence interval. Alternative parameter values were also tested: the India-specific diesel

WTW factor of 3.481 kg CO₂e/L (Smart Freight Centre, 2025), a grid factor of 0.710 kg CO₂/kWh reported for 2024–25 (CarbonNeeti, n.d.), and the matching range of electric-truck energy consumption in Table 6.

3.18 Uncertainty analysis

Probabilistic (Monte Carlo) analysis was not performed. Electric-truck energy consumption has no empirical distribution in the data, and diesel fuel economy is constant within most operators (all S1 trucks report 6.5 km/L and all S3 trucks 1.5 km/L), so a cluster bootstrap would degenerate. Uncertainty is therefore represented through scenario and range analysis.

3.19 Statistical treatment

Results are reported as medians, interquartile ranges and ranges by segment. Because observations are clustered within operators and many values are repeated, trucks are not treated as independent observations and no inferential tests are reported. Relationships are described as associations.

3.20 Data ethics and confidentiality

Operators contact details were removed from the analytical dataset. Results are reported at segment level so that individual operators cannot be identified.

4. Results

4.1 Dataset characteristics

The analytical sample comprises 92 trucks from 22 operators, all manufactured by Tata (81) or Eicher (11) (Table 2). Tippers account for half of the trucks but come from six operator groups, and segment S4 contains only four trucks. Median annual distance was 72,000 km (interquartile range 66,000–120,000 km), highest for S1 box trucks (180,000 km). For 47 included trucks, mostly tippers, the reported average load exceeded rated payload, which is consistent with overloading.

Table 2. Characteristics of the validated diesel dataset (medians unless stated).

Segment	Trucks	Operators	GVW (t)	Model year	Average load (t)	Empty share	Annual km, median (IQR)
S1 Box rigid, 28–32 t	19	5	31.4	2019	15.5	0.10	180,000 (150,000–240,000)
S2 Rigid, 14–20 t	14	8	18.4	2021	10.0	0.50	120,000 (69,000–120,000)
S3 Tipper, 47.5 t	46	6	47.5	2021	32.5	0.50	72,000 (63,000–108,000)
S4 Heavy open, 40–55 t	4	4	42.7	2018	30.0	0.20	87,000 (64,500–111,000)
S5 Medium, <14 t	9	5	12.3	2022	6.0	0.30	66,000 (60,000–72,000)
All	92	22	–	–	–	–	72,000 (66,000–120,000)

Note. IQR = interquartile range. Operators are counted within segments.

4.2 Real-world diesel baseline

Median diesel WTW emissions ranged from 0.40 kg CO₂e/km for medium trucks to 2.13 kg CO₂e/km for tippers, and from 30 to 154 t CO₂e per truck-year (Table 4, Figure 2). The 92 trucks together emitted 11,128 t CO₂e per year, of which tippers contributed 71%. The five-fold variation in per-kilometer emissions reflects reported fuel economy, which ranged from 1.5 km/L for tippers to 8.0 km/L for medium trucks.

Table 4. Diesel energy use and WTW emissions by segment (medians).

Segment	km/L	L/100 km	MJ/km	Diesel (L/yr)	Energy (GJ/yr)	kg CO ₂ e/km	t CO ₂ e/yr	g CO ₂ e/t-km (loaded trips)	g CO ₂ e/t-km (all trips)
S1 Box rigid, 28–32 t	6.50	15.4	5.5	27,692	991	0.49	88.6	35	32
S2 Rigid, 14–20 t	7.00	14.3	5.1	18,889	676	0.46	60.4	91	46
S3 Tipper, 47.5 t	1.50	66.7	23.9	48,000	1,717	2.13	153.6	131	66
S4 Heavy open, 40–55 t	3.25	31.0	11.1	27,143	971	0.99	86.9	42	33
S5 Medium, <14 t	8.00	12.5	4.5	9,429	337	0.40	30.2	131	76

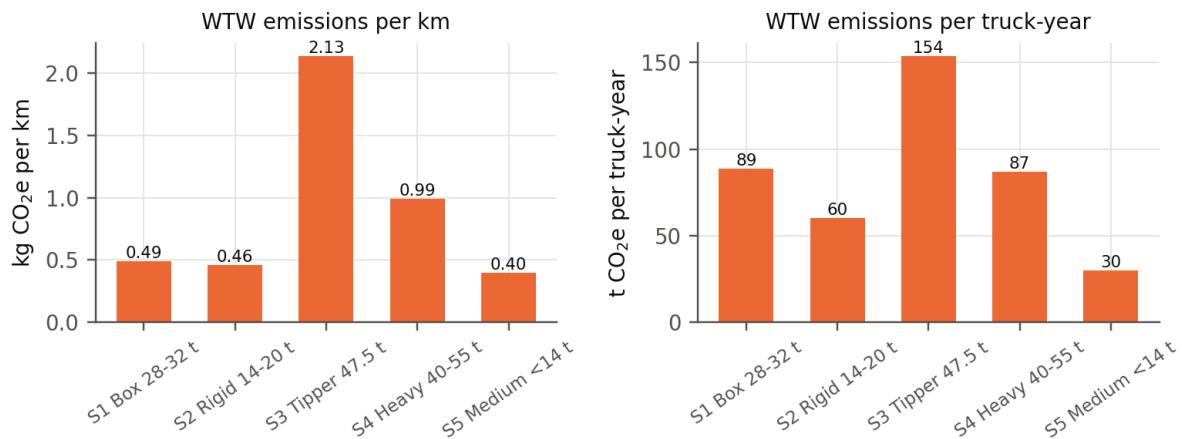


Figure 2. Diesel WTW emissions by segment: (a) per kilometer; (b) per truck-year. Medians of the validated sample.

4.3 Diesel energy and WTW emissions intensity

Per tonne-kilometre, the ranking of segments changes. Box trucks, which were highly loaded and rarely ran empty, had the lowest intensity (35 g CO₂e/t-km), while tippers and medium trucks had the highest (131 g CO₂e/t-km each). If the reported average load already includes empty trips, intensities fall to 32–76 g CO₂e/t-km, and the reduction is largest for segments with high empty running (a factor of two for S2 and S3). Tonne-km intensities are therefore reported for context but are not used in the diesel–EV comparison.

4.4 EV counterfactuals

Table 5 lists the electric trucks used. Derived specific energy consumption of the three distinct 55-t models ranged from 1.035 to 1.326 kWh/km (mean 1.176 kWh/km). The measured 18.5-t trip gave 0.859 kWh/km and the 7.5-t model 0.427 kWh/km. Segment values, and evidence tiers are shown in Table 6.

Table 5. Electric-truck technical characteristics used in the assessment.

ID	Model	GVW (t)	Payload (t)	Gross battery (kWh)	Usable (kWh)	Rated range, mid (km) / trip	SEC (kWh/km)	SEC basis	Charging (kW)
EV01	IPLT Electric Rhino 5538	55.0	41.0	282	226	193.5	1.166	Derived from manufacturer data	240
EV02	Tata Motors Prima E.55S	55.0	38.0	453	362	350.0	1.035	Derived from manufacturer data	n.p.
EV04	Ashok Leyland AVTR 55T Electric	55.0	40.0	302	242	182.5	1.326	Derived from manufacturer data	n.p.
EV09	Ashok Leyland / Switch 18.5 t rigid	18.5	10.0	200	160	1,024 kWh / 1,192 km	0.859	Measured trip	60
EV12	Tata Motors Ultra E.7	7.5	3.1	96	77	180.0	0.427	Derived from manufacturer data	44

Note. Usable energy = 80% of gross capacity. n.p. = not published. EV04 is the Ashok Leyland AVTR 55T; the Montra Rhino 5538 shares the EV01 platform and was not counted twice.

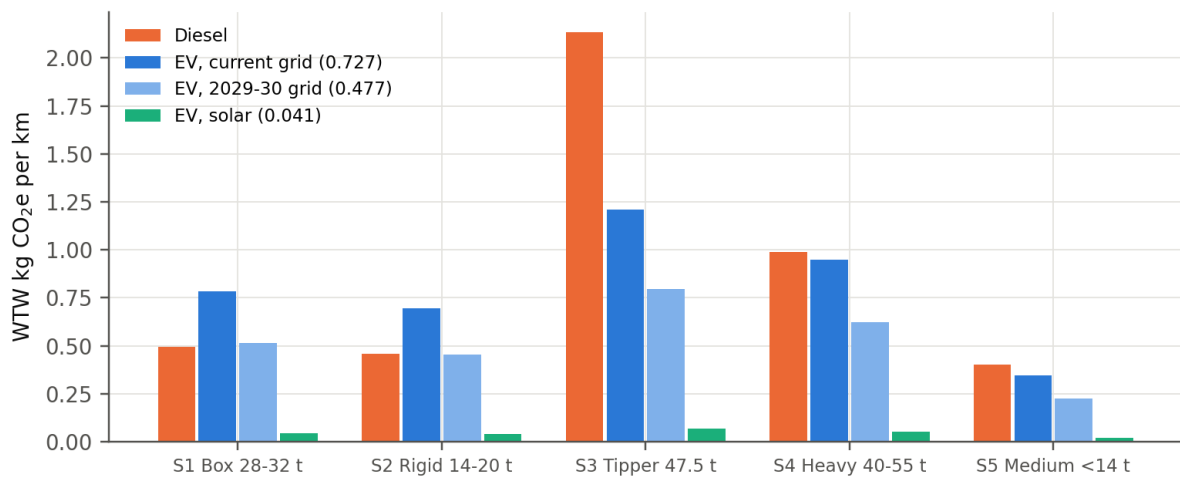
4.5 WTW diesel–EV comparison

On the current national grid, the electric counterfactual emitted less than diesel in three segments and more in two (Table 6, Figure 3). The largest reduction was for tippers (43%), followed by medium trucks (14%) and heavy open trucks (4%). For box trucks (S1) and rigid trucks (S2), electric operation increased WTW emissions by 59% and 52% respectively. Under the 2029–30 grid projection, reductions rose to 63% for tippers, 43% for medium trucks and 37% for heavy open trucks; S2 reached parity and S1 remained 5% above diesel. With solar charging, reductions were 91–97% in all segments. At median annual distance, the tipper counterfactual avoided 66 t CO₂e per truck-year on the current grid.

Table 6. Matched electric counterfactuals and WTW comparison.

Segment	Tier	SEC central (kWh/km)	SEC range (kWh/km)	Diesel kg CO ₂ e/km	EV kg CO ₂ /km, current grid	Change, current grid	Change, 2029–30 grid	Change, solar	t CO ₂ e avoided per truck-year
S1 Box rigid, 28–32 t	C	0.971	0.971–1.332	0.49	0.78	-59%	-5%	+91%	-52.6
S2 Rigid, 14–20 t	B	0.859	0.859–0.859	0.46	0.69	-52%	+0%	+91%	-28.4
S3 Tipper, 47.5 t	C	1.499	1.111–2.388	2.13	1.21	+43%	+63%	+97%	66.4
S4 Heavy open, 40–55 t	B	1.176	1.035–1.326	0.99	0.95	+4%	+37%	+95%	3.5
S5 Medium, <14 t	C	0.427	0.427–0.427	0.40	0.34	+14%	+43%	+95%	3.7

Note. Positive values are reductions relative to diesel; negative values are increases. Tier B = matched operational evidence; Tier C = modelled proxy.

**Figure 3. WTW emissions per kilometre: diesel and electric counterfactual under three electricity scenarios.**

4.6 Break-even conditions

On the current grid, the break-even specific energy consumption ranged from 0.50 kWh/km (S5) to 2.64 kWh/km (S3) (Table 7, Figure 4). The modelled electric trucks exceeded the threshold in S1 (0.97 vs 0.61 kWh/km) and S2 (0.86 vs 0.57 kWh/km) and fell below it in S3, S4 and S5. The break-even grid intensity was 1.28 kg CO₂/kWh for tippers, 0.84 for medium trucks and 0.76 for heavy open trucks, all above the current grid factor, but 0.46 and 0.48 kg CO₂/kWh for S1 and S2, which is below even the 2029–30 projection for S1. For S4, the sign of the comparison depends on which 55-t model is chosen.

Table 7. Break-even electric-truck energy consumption and grid intensity.

Segment	Diesel kg CO ₂ e/km	sEV* current grid (kWh/km)	sEV* 2029–30 (kWh/km)	SEC central (kWh/km)	EFgrid* central (kg CO ₂ /kWh)	EFgrid* over SEC range	Result across SEC range
S1 Box rigid, 28–32 t	0.49	0.61	0.93	0.97	0.46	0.33–0.46	EV higher across range
S2 Rigid, 14–20 t	0.46	0.57	0.86	0.86	0.48	0.48	EV higher across range
S3 Tipper, 47.5 t	2.13	2.64	4.03	1.50	1.28	0.80–1.73	EV lower across range
S4 Heavy open, 40–55 t	0.99	1.23	1.87	1.18	0.76	0.67–0.86	Sign depends on SEC
S5 Medium, <14 t	0.40	0.50	0.75	0.43	0.84	0.84	EV lower across range

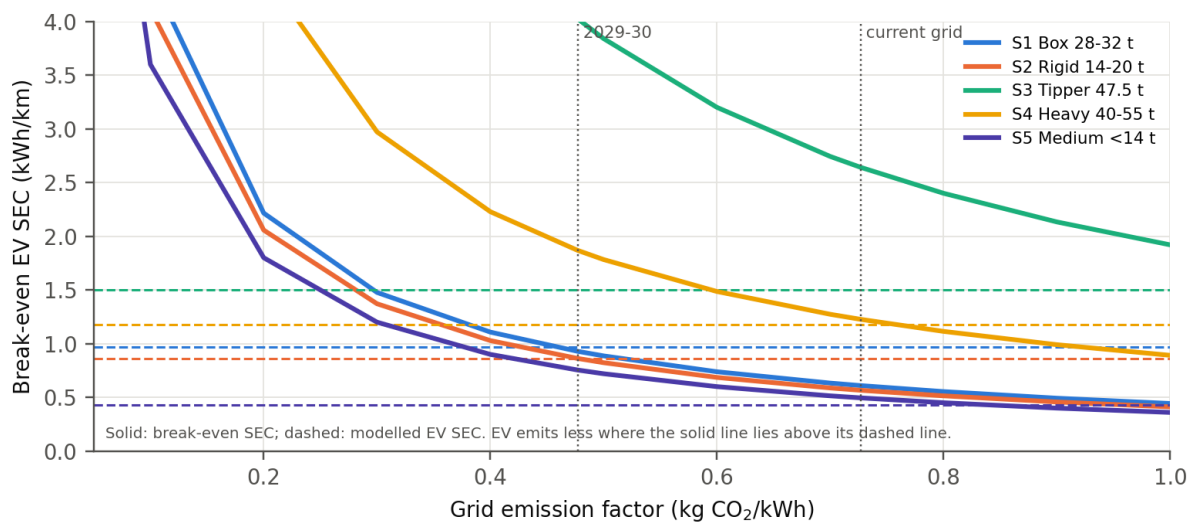


Figure 4. Break-even specific energy consumption as a function of grid emission factor (solid lines) and modelled electric-truck consumption (dashed lines). Vertical lines mark the current and 2029–30 national grid factors.

4.7 Duty-cycle feasibility

At 26 operating days per month, median daily distances were 577 km (S1), 385 km (S2), 231 km (S3), 279 km (S4) and 212 km (S5). Daily energy demand exceeded usable battery energy in seven of nine segment–model cases (Table 8, Figure 5). Only the 453-kWh 55-t model met the S4 duty cycle on a single charge (feasibility margin +26%); the same battery would also meet the tipper energy demand (+5%), although no electric tipper was available. The 18.5-t battery covered only 29% of the S1 and 48% of the S2 daily energy demand.

Table 8. Duty-cycle energy feasibility by segment and electric model.

Case	EV battery / model	Daily km	SEC (kWh/km)	Daily energy (kWh)	Available (kWh)	Feasibility margin	Single charge	Mid-shift charge (h)
S1	EV09 (18.5 t proxy battery)	577	0.97	560	160	-71%	FAIL	7.4
S2	EV09	385	0.86	330	160	-52%	FAIL	3.2
S3-a	EV01/03 battery	231	1.50	346	226	-35%	FAIL	0.6
S3-b	EV02 battery	231	1.50	346	362	+5%	PASS	0.0
S3-c	EV04 battery	231	1.50	346	242	-30%	FAIL	n.e.
S4-a	EV01/03	279	1.17	325	226	-31%	FAIL	0.5
S4-b	EV02	279	1.04	289	362	+26%	PASS	0.0
S4-c	EV04	279	1.33	370	242	-35%	FAIL	n.e.
S5	EV12	212	0.43	90	77	-15%	FAIL	0.3

Note. n.e. = not estimable because charging power is not published.

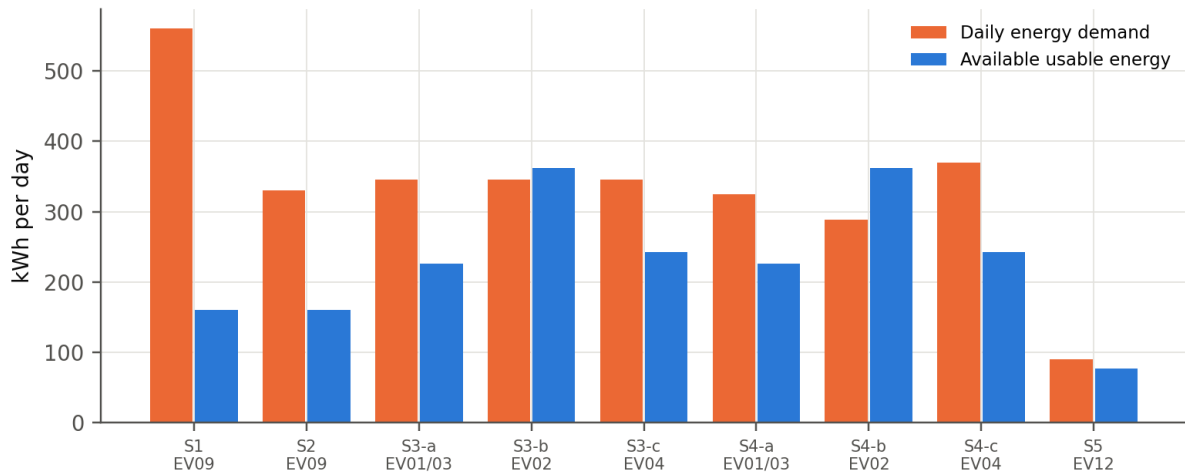


Figure 5. Daily energy demand and available usable battery energy by case.

4.8 Payload feasibility

Payload ratios were at least 1.27 for all 55-t models in S4 and exactly 1.00 for the 18.5-t truck in S2 (Table 9, Figure 7). They were 0.65 for the S1 proxy, 0.84–0.87 for the tipper proxy and 0.52 for S5, all below the conditional threshold.

4.9 Charging feasibility

Where a mid-shift charge was needed, the required charging time ranged from 0.3 h (S5) to 0.5–0.6 h (S3 and S4 with the 240-kW model), 3.2 h (S2) and 7.4 h (S1) (Figure 6). For two 55-t models, charging power is not published and the charging requirement could not be estimated.

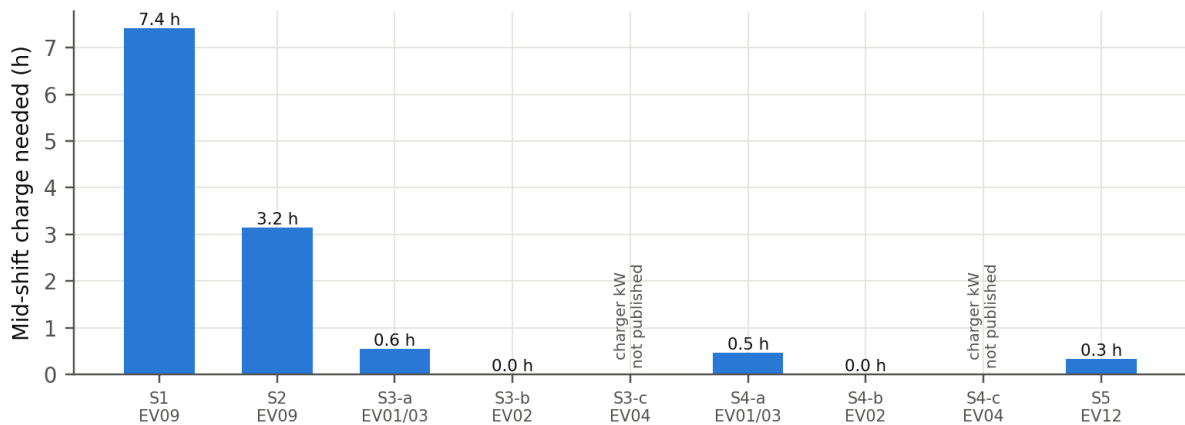


Figure 6. Mid-shift charging time required to complete the median daily duty cycle.

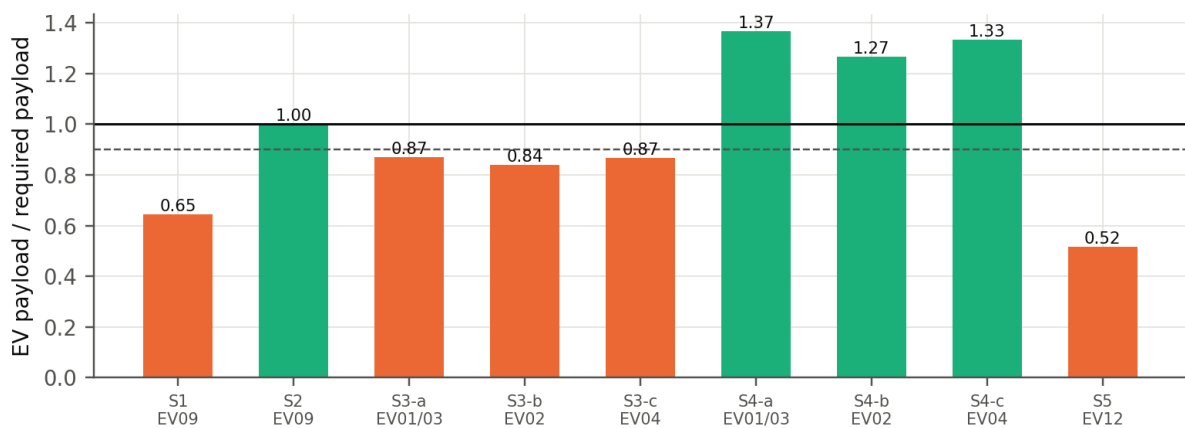


Figure 7. Payload feasibility ratio (electric-truck payload ÷ required payload). Solid line: 1.0; dashed line: conditional threshold (0.9).

4.10 Integrated readiness

Combining the constraints, S4 with the 453-kWh model was classified as high readiness; S2 and the other two S4

models were conditional on a mid-shift charge; and S1, S3 and S5 were low, because of vehicle unavailability (S1, S3) or insufficient payload (S3, S5) (Table 9).

Table 9. Constraint-based readiness by case.

Case	EV	Vehicle availability	Single charge	Mid-shift charging	EV payload (t)	Required (t)	Payload ratio	Payload	Readiness	Binding constraint
S1	EV09	FAIL: no 28-32 t EV	FAIL	dwel $\geq$ 7.4 h	10.0	15.5	0.65	FAIL	Low	Vehicle availability
S2	EV09	PASS	FAIL	dwel $\geq$ 3.2 h	10.0	10.0	1.00	PASS	Conditional	Single-charge energy
S3-a	EV01/03	FAIL: no EV tipper	FAIL	dwel $\geq$ 0.6 h	28.3	32.5	0.87	FAIL	Low	Vehicle availability
S3-b	EV02	FAIL: no EV tipper	PASS	not needed	27.3	32.5	0.84	FAIL	Low	Vehicle availability
S3-c	EV04	FAIL: no EV tipper	FAIL	n.e.	28.2	32.5	0.87	FAIL	Low	Vehicle availability
S4-a	EV01/03	PASS	FAIL	dwel $\geq$ 0.5 h	41.0	30.0	1.37	PASS	Conditional	Single-charge energy
S4-b	EV02	PASS	PASS	not needed	38.0	30.0	1.27	PASS	High	None
S4-c	EV04	PASS	FAIL	n.e.	40.0	30.0	1.33	PASS	Conditional	Single-charge energy
S5	EV12	PASS	FAIL	dwel $\geq$ 0.3 h	3.1	6.0	0.52	FAIL	Low	Payload

4.11 Application heterogeneity

Figure 8 combines the feasibility margin with the WTW reduction on the current grid. No case combines a large emissions reduction with a positive feasibility margin and an available vehicle: the tipper cases offer the largest reduction but no electric tipper exists; S4 with the 453-kWh model is feasible but reduces emissions by 16%; and the S1 and S2 cases are both infeasible on a single charge and more emission-intensive than diesel.

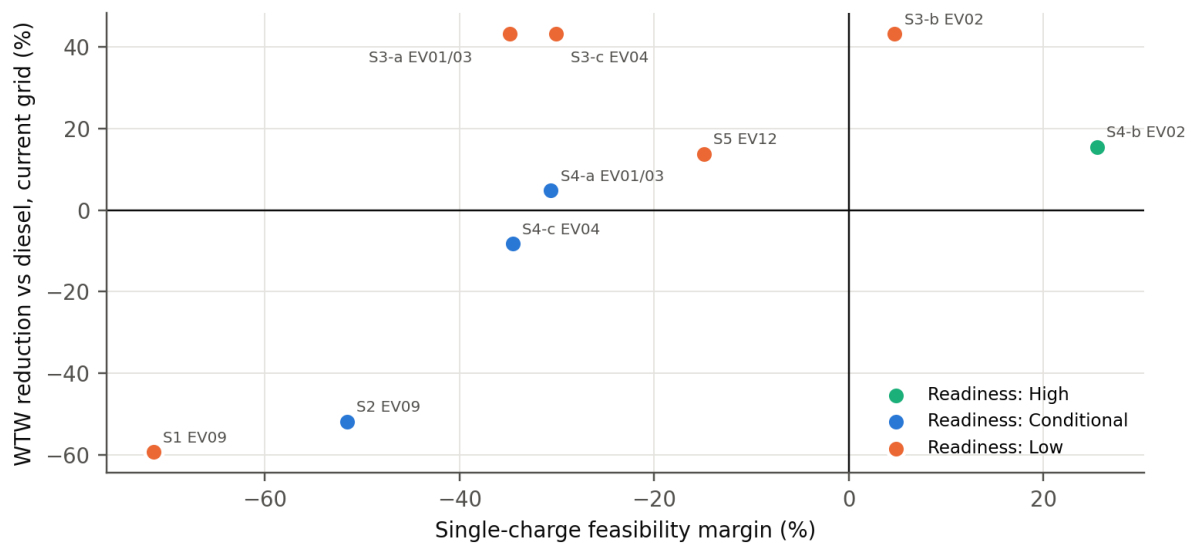


Figure 8. WTW reduction against single-charge feasibility margin, by case and readiness class (current grid).

4.12 Sensitivity analysis

The sign of the comparison was unchanged under all stress tests for S1, S2 and S3 (Table 10, Figure 9). For S1, even the lowest-emission case (grid factor or fuel economy 20% lower) left electric operation 27% above diesel; for S3, the highest-emission case (tipper factor 2.15) still gave a 10% reduction. S4 and S5 changed sign under several $\pm 20\%$ variations: S4 became worse than diesel if electric-truck consumption or the grid factor were 20% higher, and S5 if electric consumption were 20% higher. Using the India-specific diesel factor increased all

reductions (for example, S4 from 4% to 12%), and using the 2024–25 grid factor had a small effect.

Table 10. WTW changes relative to diesel under the stress tests (current grid).

Segment	Parameter	Input –20% / low	Central	Input +20% / high	Sign changes?
S1 Box rigid, 28–32 t	Diesel km/L	-27%	-59%	-91%	No
S1 Box rigid, 28–32 t	Grid factor	-27%	-59%	-91%	No
S1 Box rigid, 28–32 t	Diesel WTW factor	-99%	-59%	-33%	No
S1 Box rigid, 28–32 t	Charging efficiency	-99%	-59%	-43%	No
S1 Box rigid, 28–32 t	EV SEC	-27%	-59%	-91%	No
S1 Box rigid, 28–32 t	India diesel factor (3.481)	-46%	-59%	-46%	No
S1 Box rigid, 28–32 t	Grid factor 0.710	-56%	-59%	-56%	No
S1 Box rigid, 28–32 t	SEC matching range	-59%	-59%	-118%	No
S2 Rigid, 14–20 t	Diesel km/L	-21%	-52%	-82%	No
S2 Rigid, 14–20 t	Grid factor	-21%	-52%	-82%	No
S2 Rigid, 14–20 t	Diesel WTW factor	-90%	-52%	-26%	No
S2 Rigid, 14–20 t	Charging efficiency	-90%	-52%	-37%	No
S2 Rigid, 14–20 t	EV SEC	-21%	-52%	-82%	No
S2 Rigid, 14–20 t	India diesel factor (3.481)	-40%	-52%	-40%	No
S2 Rigid, 14–20 t	Grid factor 0.710	-48%	-52%	-48%	No
S2 Rigid, 14–20 t	SEC matching range	-52%	-52%	-52%	No
S3 Tipper, 47.5 t	Diesel km/L	+55%	+43%	+32%	No
S3 Tipper, 47.5 t	Grid factor	+55%	+43%	+32%	No
S3 Tipper, 47.5 t	Diesel WTW factor	+29%	+43%	+53%	No
S3 Tipper, 47.5 t	Charging efficiency	+29%	+43%	+49%	No
S3 Tipper, 47.5 t	EV SEC	+55%	+43%	+32%	No
S3 Tipper, 47.5 t	India diesel factor (3.481)	+48%	+43%	+48%	No
S3 Tipper, 47.5 t	Grid factor 0.710	+45%	+43%	+45%	No
S3 Tipper, 47.5 t	SEC matching range	+58%	+43%	+10%	No
S4 Heavy open, 40–55 t	Diesel km/L	+23%	+4%	-15%	Yes
S4 Heavy open, 40–55 t	Grid factor	+23%	+4%	-15%	Yes
S4 Heavy open, 40–55 t	Diesel WTW factor	-20%	+4%	+20%	Yes
S4 Heavy open, 40–55 t	Charging efficiency	-20%	+4%	+14%	Yes
S4 Heavy open, 40–55 t	EV SEC	+23%	+4%	-15%	Yes
S4 Heavy open, 40–55 t	India diesel factor (3.481)	+12%	+4%	+12%	No
S4 Heavy open, 40–55 t	Grid factor 0.710	+6%	+4%	+6%	No
S4 Heavy open, 40–55 t	SEC matching range	+16%	+4%	-8%	Yes
S5 Medium, <14 t	Diesel km/L	+31%	+14%	-3%	Yes
S5 Medium, <14 t	Grid factor	+31%	+14%	-3%	Yes
S5 Medium, <14 t	Diesel WTW factor	-8%	+14%	+28%	Yes
S5 Medium, <14 t	Charging efficiency	-8%	+14%	+22%	Yes
S5 Medium, <14 t	EV SEC	+31%	+14%	-3%	Yes
S5 Medium, <14 t	India diesel factor (3.481)	+21%	+14%	+21%	No
S5 Medium, <14 t	Grid factor 0.710	+16%	+14%	+16%	No
S5 Medium, <14 t	SEC matching range	+14%	+14%	+14%	No

Note. Positive values are reductions. For the two alternative factors, the tested value replaces the central value.

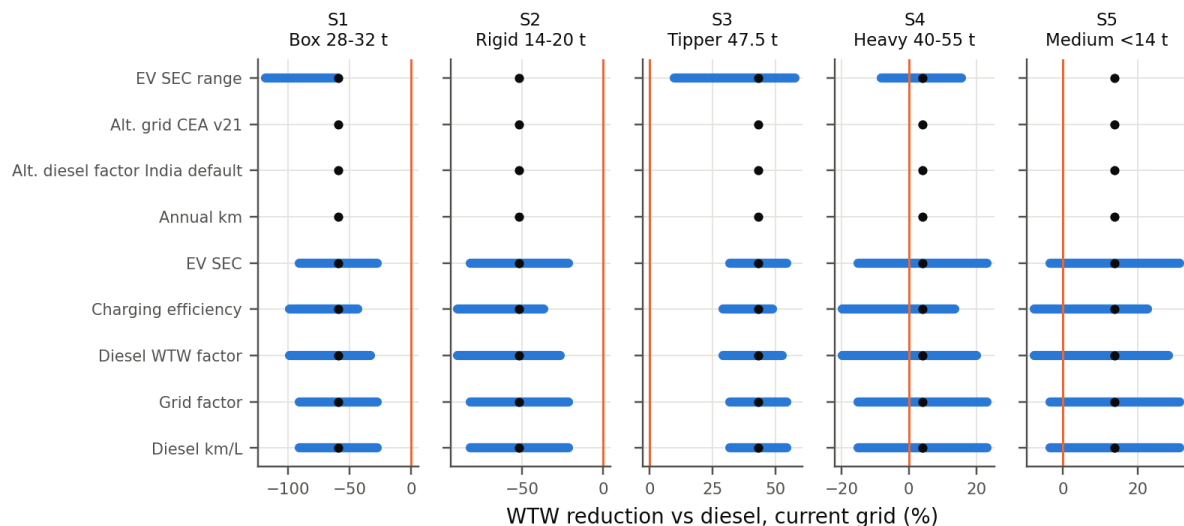


Figure 9. Range of WTW change under each stress test by segment. Dots: central estimate; vertical line: parity with diesel.

4.13 Uncertainty and robustness

The robust results are the direction of the comparison for S1, S2 and S3, the break-even thresholds and the grid-scenario ranking. The results for S4 and S5 are conditional on electric-truck efficiency, which is derived from manufacturers' rated range rather than measured, and on a single model and small samples (four and nine trucks respectively).

4.14 External deployment consistency check

The deployment register records 1,903 trucks, of which 1,272 are in the 40-t-and-above class. By application, cement accounts for 678 trucks, ports for 455 and multi-client logistics providers for 344. Screening of the recorded corridors with the assumptions of Section 3.11 gives a truck-weighted mean of 351 km per day. About 33% of trucks (633), all in port, mine or in-plant operations, have estimated daily energy within a single charge; trucks on named inter-city corridors and unrecorded regional routes would require one or two mid-shift charges. The concentration of deployment in captive, short-distance applications are consistent with the feasibility results above, but the screening rests on assumed distances and does not validate the model.

5. Discussion

5.1 Principal findings

Three findings stand out. First, the WTW outcome of electrification in the observed Indian operations is segment-specific: it ranges from a 43% reduction for construction tippers to a 59% increase for box trucks on the current grid. Second, the break-even thresholds show why: an electric truck must be efficient relative to the specific diesel operation it replaces, and efficient diesel operations set demanding thresholds (0.57–0.61 kWh/km for the rigid and box trucks). Third, technical feasibility and emissions benefit do not coincide in the observed sample; the segment with the largest benefit has no available electric vehicle, while the feasible case offers a moderate reduction.

5.2 Interpretation of WTW differences

The differences are driven mainly by diesel fuel economy per kilometre. Tippers report 1.5 km/L, which reflects heavy loads, site operation and possibly overloading; replacing such operations with electricity leaves a wide margin even on a coal-intensive grid. Box and rigid trucks report 6.5–7 km/L, which is efficient for their size and would require an electric truck of about 0.6 kWh/km to break even. That value is below the measured 0.86 kWh/km of the 18.5-t truck and below measured values for comparable European trucks (Le Corguillé et al., 2025). The results for these segments should nevertheless be read with the caveat that the reported fuel economies are operator estimates and have not been verified with fuel records.

5.3 Why freight applications differ

Applications differ along three dimensions that the analysis keeps separate: energy intensity per kilometre, which determines the WTW margin; daily distance, which determines whether a battery suffices; and payload, which determines whether an electric vehicle can carry the same freight. Annual distance affects the tonnes avoided per truck but not the sign of the comparison. Long-distance box trucks thus face two barriers at once, a narrow emissions margin and a daily energy demand three to four times the available battery, whereas captive operations with short, repeated trips face neither barrier on energy.

5.4 Comparison with previous research

The findings agree with ICCT (2024a) that battery-electric trucks can reduce emissions in India on the current grid and substantially with renewable electricity, but they qualify that conclusion: for efficient rigid and box operations, the modelled reduction turns into an increase. This is consistent with Gustafsson et al. (2021), who show that electricity-dependent options are not necessarily better than diesel on carbon-intensive grids. The

limited single-charge feasibility is consistent with Zhao et al. (2024), who found that only 23–30% of Chinese electric trucks could replace diesel trucks one-for-one, and with the finding of Liimatainen et al. (2019) that electrification potential varies strongly with vehicle size and trip length. The derived 55-t consumption (1.04–1.33 kWh/km) is of the same order as measured values for 34–40-t European trucks (about 1.14 kWh/km; Le Corguillé et al., 2025), which suggests that manufacturer-derived values are plausible but, given higher Indian payloads and temperatures, may be optimistic.

5.5 Operational implications

For operators, the break-even threshold offers a simple screening test: an electric truck is lower emission than the diesel truck it replaces only if its energy use per kilometre is below the threshold for that operation. Captive operations that return to a depot or charge during loading are the most straightforward candidates. Long-distance boxes and rigid operations would require either substantially more efficient vehicles or low-carbon electricity to achieve emissions benefits.

5.6 Industry implications

For manufacturers, published data on measured energy consumption under Indian loads, and on charging power, would allow customers to apply the threshold directly; the absence of charging-power data prevented the assessment of two 55-t models. The lack of electric tippers and of 28–32-t rigid trucks in the observed market coincides with the segment with the largest emissions potential and the segment with the highest annual distance. For charging providers, the results suggest that depot or on-site charging for captive operations and fast charging capable of delivering about 100–170 kWh within typical stops are the relevant requirements.

5.7 Policy implications

The results indicate that the emissions benefit of heavy-duty electrification in India depends on grid decarbonization: on the projected 2029–30 grid, four of five segments break even or better. Procurement of renewable electricity for charging would secure large reductions now. Because the benefit is segment-specific, support measures that target applications with low diesel fuel economy and short, repeated duty cycles are more likely to yield emissions reductions than uniform measures.

5.8 Research implications

The largest source of uncertainty is electric-truck energy consumption under Indian conditions. Measured in-use data from Indian 55-t fleets, operator fuel records for the diesel baseline, and questionnaires that define average load and empty running unambiguously would allow the framework to be applied with less reliance on assumptions.

6. Limitations

Sample and coverage. The diesel sample (92 trucks, 22 operators) comes from northern and western India and does not include cement, port or mining operations, where most electric trucks are deployed. Results are within-sample and are not nationally representative.

Operator-reported data. Fuel economy and distance are operator estimates, often repeated across an operator's trucks; fuel records were not available. The fuel economy values of 6.5 km/L (box trucks) and 1.5 km/L (tippers) drive the segment extremes.

Clustering. Trucks are clustered within 28 operator–segment groups, which precludes inferential statistics.

Electric-truck data. Energy consumption is measured for one 18.5-t trip and derived from rated range for other models; rated range may overstate real-world range under Indian payloads and temperatures. Charging power is missing for two 55-t models.

Matching. No direct (Tier A) comparison was possible. The S1 and S3 counterfactuals are modelled vehicles that do not yet exist, and the tipper duty factor is assumed.

Duty cycle. Operating days (26 per month), dwell times and return-to-base status were not observed. The deployment corridor screening uses assumed distances, speeds and turnaround times.

Physical effects. Temperature, terrain, auxiliary loads, payload dependence of electric consumption and battery degradation were not modelled.

Grid and boundary. A national average generation-based grid factor was used without transmission losses or upstream electricity emissions; regional and time-of-charging variation was not considered. Manufacturing and end-of-life emissions are excluded.

Tonne-km. The definition of average load is ambiguous; tonne-km intensities are therefore reported under two readings and are not used for the diesel–EV comparison.

Deployment register. The register mixes operating and ordered trucks, contains possible duplicate customers and has missing GVW for part of the records; it is used only for consistency checking.

7. Conclusion

RQ1. The observed diesel operations emit 0.40–2.13 kg CO₂e/km and 30–154 t CO₂e per truck-year (segment medians), with construction tippers accounting for 71% of the sample's emissions.

RQ2. On the current national grid, the matched electric counterfactuals reduce WTW emissions for tippers (43%), medium trucks (14%) and heavy open trucks (4%) and increase them for 14–32-t rigid and box trucks (52–59%).

RQ3. The benefit varies more between segments than between most parameter assumptions; it increases substantially on the projected 2029–30 grid and exceeds 90% with solar charging in all segments.

RQ4. Only one 55-t model covers the median heavy open-truck duty cycle on a single charge. Most other cases require a mid-shift charge, and payload is insufficient for the tipper and medium-truck proxies. About one-third

of deployed trucks operate captive duty cycles that are compatible with a single daily charge.

RQ5. Electrification yields a WTW advantage on the current grid only if electric-truck energy consumption is below 0.50–2.64 kWh/km, depending on segment. These thresholds do not depend on annual distance and are most sensitive to diesel fuel economy and grid intensity.

The analysis establishes that the emissions case for heavy-duty electrification in India is conditional on the efficiency of the electric vehicle relative to the diesel operation it replaces, and on the carbon intensity of the electricity it uses. Results for 40–55-t and medium trucks remain conditional on measured electric-truck performance. Future research should apply the break-even framework to measured Indian electric-truck data and to diesel baselines from cement, port and mining operations.

Data availability

The calculation workbook, including raw inputs, cleaning rules, parameters, calculations, figure data and a result-provenance register, is provided as supplementary material. Operator identities are withheld.

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