nature energy

Analysis

https://doi.org/10.1038/s41560-024-01602-x

Challenges and opportunities in truck electrification revealed by big operational data

Received: 17 July 2023

Accepted: 11 July 2024

Published online: 12 August 2024

Check for updates

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The electrification of trucks is a major challenge in achieving zero-emission transportation. Here we gathered year-long records from 61,598 electric trucks in China. Current electric trucks were found to be significantly underutilized compared with their diesel counterparts. Twenty-three per cent of electric delivery trucks and 30% of semi-trailers could achieve one-on-one replacement with diesel counterparts, while on average 3.8 electric delivery trucks and 3.6 electric semi-trailers are required to match the transportation demand that is served by one diesel truck separately. For diesel trucks that are capable of one-on-one replacement, electric trucks have 15–54% and 1–49% reductions in cost and life-cycle CO_2 emissions, respectively. Enhancements in usage patterns, vehicle technologies and charging infrastructure can improve electrification feasibility, yielding cost and decarbonization benefits. Increased battery energy densities with optimized usage can make one-on-one electrification feasible for more than 85% of diesel semi-trailers. In addition, with cleaner electricity, most Chinese electric trucks in 2030 will have lower expected life-cycle CO_2 emissions than diesel trucks.

The comprehensive mitigation of carbon dioxide (CO_2) emissions from the transport sector is essential for achieving carbon neutrality. It was estimated that heavy-duty vehicles (HDVs) accounted for approximately 30% of all transport CO_2 emissions globally in 2020[1]. As fleet electrification is recognized as an important solution to decarbonize the transportation sector, many countries and regions have set ambitious targets to drive electrification in HDV fleets[2–6]. In California (US), the Advanced Clean Fleets regulation requires that truck manufacturers increase the market share of zero-emission vehicles to 100% by 2036[3]. Led by California, the US government has set 30% and 100% sales targets for zero-emission medium-duty (MD) and heavy-duty (HD) vehicles by 2030 and 2040, respectively[4]. The new HDV CO_2 emission standard proposed by the European Commission sets CO_2 emission reduction targets of 45% by 2030 and 90% by 2040 compared with the 2019 levels for HDV fleets[5], which is also expected to drive the deployment of electric trucks (ETs). In China, no official national market target for ETs has been announced, but the China Society of Automotive Engineers[6] has proposed a future

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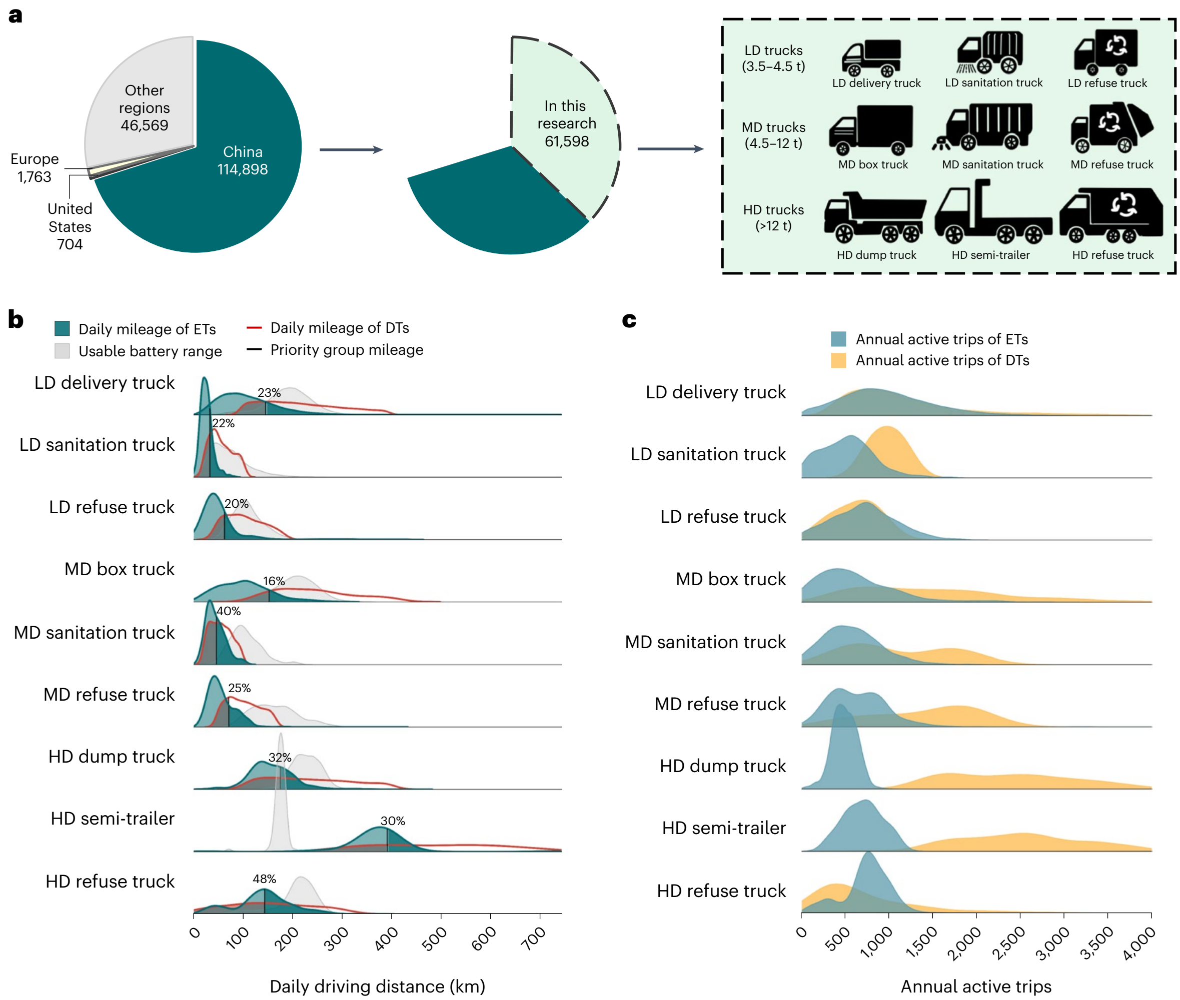

Fig. 1 | Vehicle stock and usage patterns of ET fleets. a, Global ET stock in 2021[27] (left), number of ETs in this study (middle) and categorization of the ET samples (right). **b**,**c**, Daily mileage (**b**) and annual distribution of active trips (**c**) for DT and ET fleets. The UBR of ETs is estimated based on battery capacity and real-world electricity consumption, indicating the maximum mileage after full charging (see Methods for details). In **b**, the priority groups in the ET/DT fleets (that is, ETs/DTs feasible for one-on-one replacement) are highlighted with dark shadows under the green/red curves, and the percentage values indicate the current priority group ratios.

roadmap for developing new energy vehicles, which includes the promotion of ETs.

Despite the great ambition to promote ETs, their current sales are at a nascent stage across the world compared with the soaring number of electric cars or buses. In 2021, sales of ETs accounted for 1.5% of all new trucks registered in China[7], which was substantially lower than the shares of electric cars (16%) and buses (8.9%)[7]. In 2020, only 0.4% of new MD and HD truck registrations in the European Union and 0.03% of HD truck registrations in the United States were zero-emission vehicles[8]. As no real-world performance derived from large-scale deployed ETs has been evaluated or reported, the market remains conservative towards ET deployment because of mileage concerns[9–11], battery and payload limitations[12,13] and the limited availability of adequate charging infrastructure[14–16]. Regarding decarbonization effects, the life-cycle CO_2 emissions of ETs remain uncertain due to the lack of real-world energy consumption data across different truck categories[17–20]. Previous studies have relied heavily on theoretical calculations and scenario analysis to estimate the vehicle-level cost and emissions of ETs compared with their diesel counterparts[21–25], often ignoring the fact that one ET may have a different transport capability than its respective diesel truck (DT) model.

As the current host of the world's largest ET fleets, China provides a timely opportunity for analysing the actual usage profiles of the early-batch ETs[26–29]. In this study, we gathered the year-long real-world monitoring records from more than 60,000 ETs, which accounted for more than one-third of the global stock in 2021 (Fig. 1a). Comparing the usage patterns from DT and ET datasets, we identified current challenges for ET deployment that are related to their usage patterns. We leveraged the big data to derive two usage metrics as feasibility indicators: the 'priority group ratio', which denotes the ratio of vehicles that are feasible for one-on-one replacement, and the 'replacement rate', which denotes the average number of ETs needed to replace one DT after matching fleet-level transport demand. Integrating the usage patterns with life-cycle modelling, we evaluated the actual individual- and fleet-level costs and decarbonization effects of truck electrification by category. To identify various opportunities for comprehensive truck electrification, future projections on technology improvements (including battery improvement, charging infrastructure and sustainable electricity) under optimized usage reveal great potential but differentiated improvement orientations are needed for different ET fleets to achieve CO_2 emissions–cost synergy.

Difference in usage patterns of electric and diesel trucks

In this research we gathered real-world activity recordings from 61,598 ETs in China during 2021, which included detailed trip-level information with energy consumption and charging records. The ETs in the dataset

 https://doi.org/10.1038/s41560-024-01602-x

account for more than one-third of the global stock in 2021 (Fig. 1a). At the same time, we also collected the on-board monitoring (OBM) records of 55,411 DTs in China for comparative benchmarking. We categorized both ETs and DTs by vocation and gross vehicle weight (GVW). In total, nine fleets were evaluated in this research, as shown in Fig. 1a.

From the large-scale real-world dataset, we observed that ETs had significantly lower usage intensity compared with DTs. In Fig. 1b, we compared the daily mileage distributions between individual DTs and ETs, along with the usable battery range (UBR), which represents the maximum mileage of the ET after full charging. Compared with their DT counterparts, all ET categories showed significantly lower daily mileages. Apart from electric HD refuse trucks (91%), MD sanitation trucks (80%) and HD semi-trailers (75%), the ratios of fleet-average daily mileage for ETs relative to DTs were below 70%, ranging from 42% (MD box trucks) to 69% (HD dump trucks). For the light-duty (LD) segments (GVW < 4.5 t), electric delivery trucks had the largest population among all ETs. LD diesel delivery trucks could run approximately 200 km per day on average. The average daily mileage of electric delivery trucks was merely 109 km. For the HD segment (GVW > 12 t), semi-trailers and dump trucks shared the largest stock number of ETs. The real-world data indicated that electric semi-trailers and dump trucks ran, respectively, 372 km and 158 km on average, equivalent to 69% and 75% of the levels of the respective DT fleets.

The reasons for the underusage of ETs included the limited battery capacity, range anxiety and different task assignments compared with DTs. We found that ETs were underused compared with their maximum potential, as could be inferred from their short daily mileage and insufficient battery use. Except for HD semi-trailers, the average daily mileages of all ETs were far lower than the UBRs (Fig. 1b and Supplementary Table 1), which indicated sufficient opportunities for increasing their use intensity (that is, the daily mileage or active trips) without extra charging. For some ET fleets, such as electric refuse and sanitation trucks, the UBRs can readily satisfy the daily travel demand of DTs. For LD delivery trucks and MD box trucks, the UBRs of ETs were lower than the daily mileage of their diesel counterparts, suggesting that these ETs will require additional charging within the driving day to reach the daily mileage of DTs. Notably, the average daily mileage of HD electric semi-trailers exceeded their average UBR, indicating that frequent charging (on average 2.4 times per day) had already become the solution to addressing the range issue. Supplementary Figure 1 shows the state of charge (SOC) distribution at the start of charging. At present, most of these distributions (except for the HD semi-trailer) peak at around 40–60%, suggesting that the range anxiety of ET drivers led to the actual active battery range being limited to approximately half of the battery capacity.

Another factor contributing to the low usage intensity of ETs was their limited driving frequency (Fig. 1c), and the gap between ET and DT fleets increased with GVW. For example, electric LD delivery trucks had 17% fewer annual active trips compared with their diesel counterparts, while electric HD semi-trailers had 71% fewer active trip numbers relative to diesel semi-trailers. Despite being regulated by the same set of maximum speed limits on roads, there existed differences in the operational speed of ETs and DTs, as shown in Supplementary Fig. 2, which will potentially influence the freight efficiency of ETs. For low-speed DT fleets, such as sanitation and refuse trucks, the gap in speed was smaller, and electric LD refuse trucks even can achieve higher speeds. However, for high-speed DT fleets for which delivery efficiency is more important, such as LD delivery trucks, MD box trucks and HD semi-trailers, the average operational speed of ETs was much lower than their diesel counterparts.

Despite the underusage of ETs at the fleet level, we observed that some ETs can achieve the daily mileage of a certain proportion of low-mileage DTs in each truck category. These DTs, which are already replaceable with a single current ET without further usage optimization or technological improvement, are prime candidates for early electrification (referred to as the 'priority group' in this research). Currently, as shown in Fig. 1b, the proportion of vehicles in the priority group varied from 16 to 48%. The percentages of DTs that can be replaced on a one-on-one basis with ETs are 23% and 30% for LD delivery trucks and HD semi-trailers, respectively. The priority group ratio serves as one possible indicator for quantifying the electrification feasibility within each truck category. We now examine how usage optimization and technological improvement could increase the ratios of priority group vehicles in the following section.

Emission and cost comparisons between individual electric and diesel trucks

Cost and CO_2 emissions are the primary indicators for assessing the impacts of electrification. Here we evaluated the total cost of ownership (TCO) and life-cycle CO_2 emissions of individual ETs and DTs by fleet on the basis of real-world vehicle usage, energy consumption (Supplementary Fig. 3 for ETs; Supplementary Fig. 4 for DTs) and CO_2 emission intensities in China. As shown in Fig. 2a, although ETs can achieve considerable well-to-wheels (WTW) CO_2 emission reductions for most fleets in most of the grid regions (Supplementary Fig. 5a), carbon emissions associated with battery supply chains and lower vehicle mileage lead to a mixed profile in life-cycle decarbonization effects for ETs compared with DTs. Electric sanitation trucks have higher life-cycle CO_2 emissions compared with their respective DTs because of higher vehicle-cycle CO_2 emissions from lower mileage, whereas the other electric fleets achieve 8–37% decarbonization benefits. The vehicle-cycle attributes more in life-cycle CO_2 emissions for ETs (17–40%) than for DTs (2–18%). With cleaner electricity in China after 2030[30], lower carbon intensities of electricity and material production are expected to effectively decarbonize ETs. All ETs apart from MD sanitation trucks will have life-cycle decarbonization effects over DTs. With 100% renewable electricity during the operational stage and supply chains of vehicle materials, ET fleets will have 70–91% life-cycle CO_2 emission savings compared with DTs (Supplementary Fig. 6).

ETs generally have higher purchase costs (including subsidies) and lower mileages but benefit from lower fuel (electricity) costs. The gap in the purchase costs can be almost fully compensated by the savings in fuel costs. From a fleet-average comparison, currently, ETs in five out of nine categories already have lower TCO than their diesel counterparts (Fig. 2b), in which the three HD fleets and LD delivery trucks can achieve 12–37% cost savings. For LD sanitation and the MD fleets, the savings on fuel costs are constrained by their low mileages, which result in the higher TCO for ETs compared with DTs. We find synergy in CO_2 emission reductions and cost savings for electrifying LD delivery trucks, LD refuse trucks and the three HD fleets when comparing individual life-cycle CO_2 emissions and TCO, although ETs have lower mileages.

Furthermore, compared with the respective DTs that are feasible for one-on-one replacement, ETs in the priority group have lower TCO (by 15–54%) and CO_2 emissions (by 1–49%) across all truck categories, as shown in Supplementary Fig. 7. Because ETs within the priority group have higher usage intensity compared with the fleet average, they have lower material-cycle CO_2 emissions and receive more benefits from low electricity prices. In particular, if comparing the ETs in the priority group with all of the DTs in the same category, except for sanitation trucks, all truck categories could receive positive decarbonization and cost benefits from electrification. This suggests that feasibility issues, which are mainly reflected by underusage, pose a greater barrier to truck electrification than either cost or environmental considerations. In the following section, we will quantify the impact of optimizing usage on the priority ratio and electrification effects.

Enhancing fleet electrification effect by optimizing usage

The priority group analysis and the observed usage pattern difference between ETs and DTs suggest that the one-to-one replacement

https://doi.org/10.1038/s41560-024-01602-x

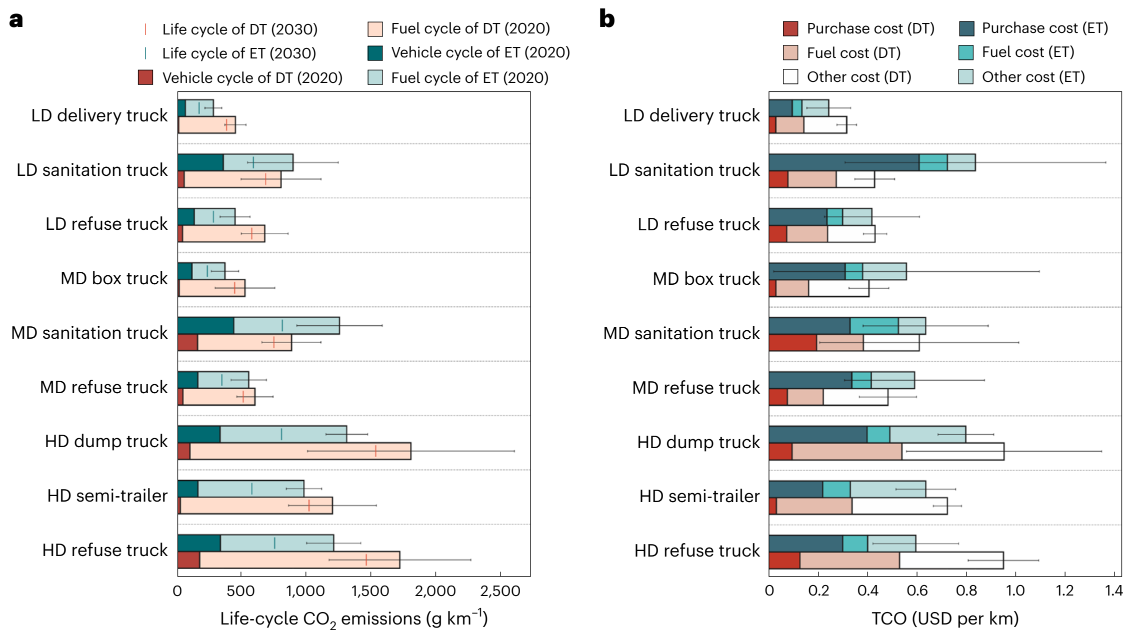

Fig. 2 | Life-cycle CO_2 emissions and TCO of individual ETs and DTs. a, Average life-cycle CO_2 emissions of individual ETs and DTs by fleet. **b**, Average TCO of individual ETs and DTs by fleet in 2020. USD, US dollars. Data are presented as mean values ± standard deviation. Error bars refer to the variance of different vehicles, and vehicle numbers are listed in Supplementary Table 5.

between ETs and DTs is only feasible for a limited subset of vehicles. Hence, a more comprehensive understanding of the effects of fleet-level electrification is essential to anticipate the wide adoption of ETs in the future. In this research we examined both the vehicle-level usage metric of the priority group, and the fleet-level metric—the replacement rate—derived from large-scale real-world datasets. These usage metrics were integrated with life-cycle modelling to quantify the electrification effects for both early adopters and the fleet at large under different optimization scenarios.

Under the assumption that the total work demand for a truck fleet is independent of the vehicle powertrains, we developed a trip-chain-based method to evaluate the number of ETs (the replacement rate) needed on average to replace one DT and evaluated the corresponding TCO and life-cycle CO_2 emissions after usage normalization (see Methods for more details). The results of the fleet-level usage normalization (Fig. 3) show that, if ET drivers keep current usage patterns, on average, 3.8 electric delivery trucks and 3.6 electric semi-trailers are needed to replace one current diesel counterpart. As shown in Supplementary Fig. 8, most replacement rate distributions have long tails from high-mileage DTs. Considering additional vehicle-cycle CO_2 emissions and costs, almost all ET fleets with current usage profiles will lose either the cost or life-cycle CO_2 advantage compared with DT fleets after usage normalization (Fig. 3 and Supplementary Fig. 9).

Improving vehicle usage can effectively raise the priority group ratio, cut down the replacement rate and shrink the deficits in CO_2 and TCO. Except for MD sanitation trucks, HD semi-trailers and HD refuse trucks, by increasing the average battery use to 85% SOC (defined as the 'optimized usage'), all other ET fleets can have one-on-one priority group ratios that are higher than 49% (Supplementary Table 2) and achieve a life-cycle CO_2 emission balance with diesel counterparts (Fig. 3 and Supplementary Fig. 9). These ET fleets are also feasible for achieving a TCO balance with their usage intensity increased to no more than that of DT fleets. For example, for LD delivery trucks, with battery usage at 85% SOC, an additional 34% of LD delivery trucks can match one-on-one replacement with their diesel counterparts (Supplementary Table 2), and the replacement rate will decrease from 3.8 to 2.0 if charging accessibility can be guaranteed (Fig. 3a). Building on 85% battery use, increasing the annual active trips by 52% can further reduce the replacement rate of ETs and achieve a TCO balance. However, for electric HD semi-trailers, the current battery usage rate is high (82%) with limited room for usage improvement for existing electric semi-trailer vehicle models. Even increasing the usage intensity to that of diesel semi-trailers, it is still not possible for the electric semi-trailers to achieve a cost or life-cycle CO_2 balance if the work demand is matched. Thus, further technology improvements (for example, higher battery energy densities) should be considered for electric HD semi-trailers to achieve cost and decarbonization benefits beyond usage optimization.

Improving truck fleet electrification benefits in the future

Optimizing usage reveals the maximum potential of current ET models and proves the need for technological improvements, battery and charging improvements in particular, to enhance the feasibility of ETs for high-energy-demand fleets (for example, HD semi-trailers). In this context, we evaluated the influence of technological improvements and more sustainable electricity mixes on electrification feasibility and effects in the future. On the basis of optimized usage (an average battery use of 85% SOC), the fleet-level replacement rate and the corresponding life-cycle CO_2 emissions and TCO are assessed to identify the future electrification opportunities under different scenarios.

Battery improvements, such as an increase in the battery capacity or energy density, will enable ETs with higher mileages beyond optimized usage, thus increasing the fleet priority group ratios and reducing the replacement rates. An increase in the battery energy density to 220 Wh kg^{-1} (with an unchanged battery mass) will result in the priority ratios exceeding 70% for all truck categories (Supplementary Table 2a). Notably, for HD semi-trailers, the priority ratio will increase from 36 to 87%, confirming that a limited battery capacity is the principal constraint of electric HD semi-trailers. An increase in the battery energy density is also beneficial for the TCO and life-cycle CO_2 of LD delivery trucks and HD semi-trailers (Fig. 4) by effectively decreasing the replacement rate. Only with an increase in the battery density can the electric LD delivery truck fleet receive both cost and CO_2 advantages

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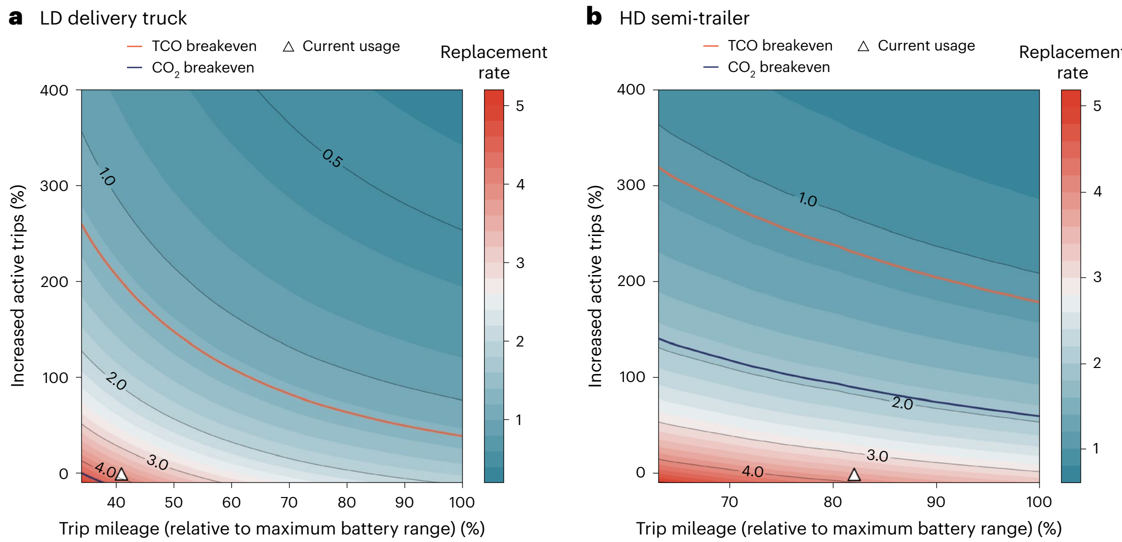

Fig. 3 | Replacement rates after fleet usage normalization. The replacement rate is the number of ETs needed on average to replace one DT to match the fleet-level freight demand. **a,b,** Replacement rate results under current and optimized usage intensities for LD delivery trucks (**a**) and HD semi-trailers (**b**). TCO breakeven and CO_2 breakeven are the replacement rates at which ET fleets have cost and life-cycle CO_2 balance with the respective DT fleets. Trip mileage and increased active trips influence the usage intensity independently.

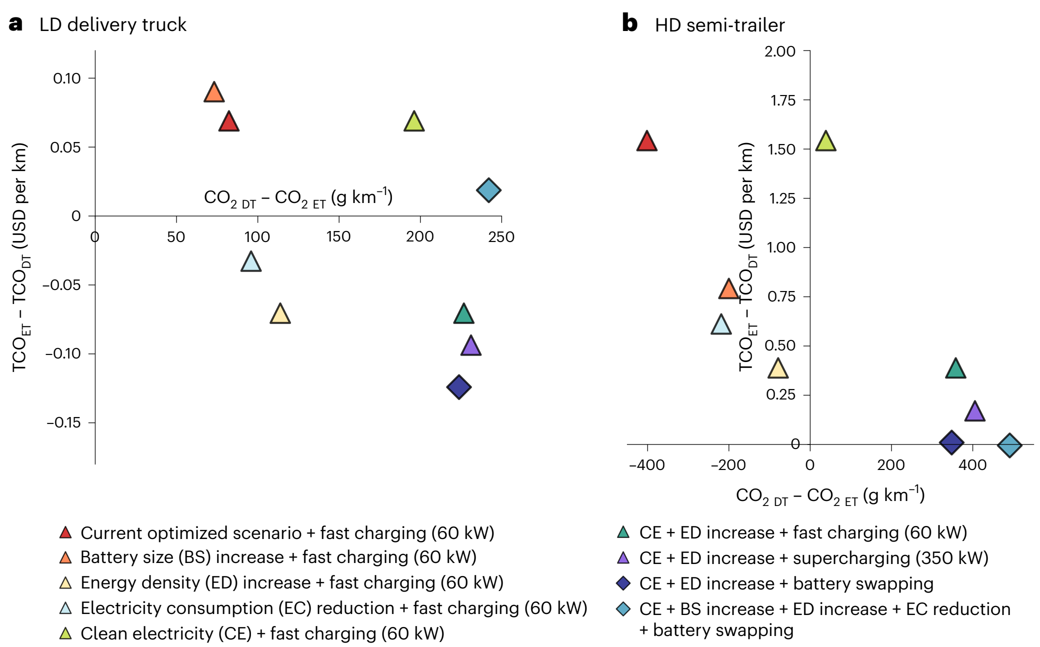

Fig. 4 | Future electrification effects under different scenarios for ETs. **a**,**b**, Expected effects for LD delivery trucks (**a**) and HD semi-trailers (**b**) under different electrification scenarios. The current optimized scenario is the current scenario with optimized usage intensity; battery size (BS) increase denotes an increase in battery capacity of 50% (with unchanged energy density and unit cost); energy density (ED) increase denotes an increase in battery energy density to 220 Wh kg^{-1}; electricity consumption (EC) reduction denotes a decrease in ET electricity consumption of 25%; clean electricity (CE) refers to using sustainable electricity after 2030; supercharging enables Level 3 charging infrastructures. All scenarios include optimized usage (average battery use to 85% SOC) for ETs and improvements in fuel economy for DTs. See Methods for more scenario design details.

over DTs. By contrast, an increase in the battery energy density has marginal effects on fleets with a shorter transport demand (for example, refuse trucks) because current battery capacities can almost cover the demand with optimized usage. Increasing the battery capacity with the current battery technology (with an unchanged energy density and unit cost) will reduce the truck payload but effectively increase the mileage. A 50% increase in battery size will lead to a 7% payload reduction for electric semi-trailers, yielding an 11% CO_2 and a 25% cost reduction compared with the current optimized scenario. However, this shows negative effects on both the life-cycle CO_2 and TCO for the other fleets (Fig. 4 and Supplementary Fig. 10).

Sustainable electricity is the key and most effective approach for reducing the life-cycle CO_2 emissions of ETs. By transitioning to the lower-carbon-intensity electricity generation, most electric fleets will have large decarbonization effects compared with DTs (Fig. 4 and Supplementary Fig. 10). Battery swapping and Level 3 supercharging will also enable ETs with comparable transport capabilities compared with DTs, which is particularly useful for reducing costs with electric HD semi-trailers. With a battery capacity increased via an energy density increase to 220 Wh kg^{-1} and a 50% size increase for battery swapping, both additional batteries will be needed (Supplementary Table 3) and TCO for a single battery will decrease for semi-trailers. As a result, with 25% reduction in electricity consumption, future electric HD semi-trailers can achieve cost balance with diesel counterparts through battery swapping (Fig. 4). As summarized in Fig. 4 and Supplementary Fig. 10, all LD and HD electric fleets will have opportunities for receiving TCO–CO_2 synergy effects in the future, but truck manufacturers and relevant stakeholders should understand that differentiated improvement strategies are needed to achieve such future cost and decarbonization effects.

Discussion

In our life-cycle modelling, numerous economic and technical parameters (for example, the battery pack price, the reduction of energy consumption, subsidies and so on) influence the TCO and CO_2 emission outcomes. Sensitivity analysis shows that energy consumption savings (electricity consumption reductions for ETs and fuel consumption reductions for DTs) are the most influential factor for the modelling results, as shown in Supplementary Fig. 11. For ET fleets, a 10% reduction in electricity consumption will result in a 1.2–3.1% reduction in TCO and a 4.9–7.6% reduction in life-cycle CO_2 emissions. In addition, as there are no real-world data available on battery degradation, we also assessed the TCO and CO_2 implications if ETs required a battery replacement within their lifespan (Supplementary Fig. 12). Except for MD sanitation trucks, changing one battery within the ET lifetime will cause an increase in TCO of US$0.33–1.41 per km (13.8–28.7%) and increase in CO_2 emissions of 19.5–82.9 g km^{-1} (3.6–9.2%). Except for battery replacement, energy consumption savings and a reduction in the battery pack price will bring marginal effects on the electrification effects of LD delivery trucks and HD semi-trailers with usage optimization and technological improvements (Supplementary Figs. 11 and 13).

The lower usage intensity of ETs compared with DTs is one of the greatest challenges that we have identified regarding the large-scale deployment of ETs, which is also the key reason for the high TCO. The priority group analysis demonstrates that current high-mileage ETs can achieve both economic and environmental benefits over their respective DTs, which emphasizes the need for enhancing ET usage as a primary step towards effective electrification. Our analysis attributes the low usage intensity to two different aspects: the underusage of ETs and the limitation of batteries. The real-world performance of ETs derived from the dataset reveals that there are sufficient opportunities for most ET fleets to improve current usage on both driving mileage and charging, which suggests that the underusage may be the result of both psychological effects (such as well-documented range anxiety[28,31,32]) and insufficient task assignment (Supplementary Note 3). Therefore, alongside fundamental technological and infrastructure improvements for effective electrification, it is crucial to design policy interventions and implement education initiatives for ET drivers and fleet operators, to help them alleviate concerns over electrification[23] and thus improving ET usage. However, for some high-energy-demand fleets (for example, HD semi-trailers), improvements in battery technology are needed to raise the vehicle mileage and enhance the feasibility of electrification.

Some previous publications have observed the low mileage of ETs[33–35] but have not successfully linked it to electrification cost or decarbonization effects. The usage intensity analysis performed in this study reveals that a one-to-one vehicle comparison between the TCO and life-cycle CO_2 emissions of ETs and DTs is only representative of a small subset of fleets (priority fleets), and fleet-level comparison with usage intensity normalization is needed to quantify the effects for the wide adoption of ETs in the real world.

It is part of the global agenda to deploy zero-emission vehicles in the trucking sector[3–6]. Principal markets such as the United States and Europe have provided higher purchase incentives[36,37] to improve the cost competitiveness of ETs. For instance, the California Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project (HVIP)[36] could cover more than 80% of the purchase price gap, whereas European countries have offered maximum price gap incentives of between 30 and 80% (ref. 37). Recently, demonstration data of daily mileage and battery status from ET fleets in California (18 vehicles in total)[38] became available to understand their real-world usage profiles, cost effects and decarbonization benefits (Supplementary Note 4). We noticed that the purchase incentives from HVIP played an important role in reducing the TCO of ETs in California[36], with which electric delivery trucks and semi-trailers (such as Tesla Semi trucks) can achieve cost parity with diesel counterparts (Supplementary Fig. 18). However, similar to Chinese ET fleets, the real-world performance of Class 6 ETs (categorized as MD box trucks in this study) in California also revealed underusage and resulted in higher TCO values than the diesel counterparts. Remarkably, Tesla Semis operating in California offered a great example of electrifying long-haul freight trucks. Equipped with large-capacity batteries (approximately 850 kWh), an efficient aerodynamic design and access to superchargers, Tesla Semis have achieved an average daily mileage of 945 km (Supplementary Fig. 17) with a low electricity consumption (~125 kWh per 100 km; details in Supplementary Note 4)[38], which could be used in the one-on-one replacement of diesel semi-trailers for long-haul transport. Currently, ETs used for long-haul operation are scarce in China. Most policies and investments have focused on encouraging and advancing infrastructure constructions, such as battery swapping or supercharging stations. The demonstration experience for Tesla Semis of PepsiCo in California[38] and our scenario analysis both highlight the importance of progress in battery technology and improvements in energy efficiency for the successful electrification of long-haul freight.

Our analysis highlights the importance of leveraging big data to inform decision-making during the electrification process. Most policy or market decisions so far have been driven by aggregate general statistics such as the average, which in statistical terms is the first-order moment of the involved distributions. With big data, we can look into each sample of the distribution and gain a much more nuanced understanding of the situation. For example, the individual-level usage data enable us to accurately identify the features of DT candidates that are feasible for the early adoption of electrification; with detailed large-scale trip chains, we can accurately evaluate the fleet-level electrification effects after usage normalization, which are considerably different from the vehicle-level comparison. Furthermore, big data also shed light on future policy-making and strategic planning. Priority ratios under usage optimization and technological improvements indicate the appropriate penetration targets in both the short and long term for different truck categories. A sales target exceeding 30% will be low-hanging fruit for most Chinese fleets apart from semi-trailers before 2030, while it is promising to have ET sales of more than 80% for all categories with a battery density increase (see Supplementary Table 2) in the future. Such sales targets and associated incentives, which have already been announced for electric passenger cars, have not been released for China's truck market. As electrification is one of the most important approaches for the low-carbon energy transition, the benefit of big data analysis is not confined to truck electrification: big data has great potential to unlock insights and inform more effective policies and practices on other related topics, such as the ban on internal combustion engine vehicles, heat pump installation for sustainable buildings and renewable power plant operations. However, the current scarcity of available data on cost and usage still poses a challenge and points to the need for encouraging the increasing availability of real-world data globally, similar to those provided by the North American Council for Freight Efficiency[38]. With granular big data, decision makers can come to more informed and targeted decisions that lead to improved efficiency, reduced costs and better environmental outcomes.

https://doi.org/10.1038/s41560-024-01602-x

Methods

Data acquisition

The real-world monitoring profiles of 61,598 ETs (model year 2018–2021) were obtained from the open laboratory of China's National Big Data Alliance of New Energy Vehicles. The samples of ETs were distributed in seven provincial regions across China (Beijing, Guangdong, Hebei, Jiangsu, Shanghai Sichuan and Zhejiang). The year-long data records ranged from November 2020 to October 2021, and included 201 million trips and 51 million charging events—Supplementary Table 4 provides data examples of driving and charging events. We matched vehicle specifications by vehicle model and categorized the ETs on the basis of the GVW and use purpose. Supplementary Table 5 summarizes the number of ET samples for each fleet category, and we included only the categories with more than ten vehicle samples (nine categories in Fig. 1a) in the analysis.

For DTs as the benchmark, we gathered the OBM data from more than 55,000 DTs with the same range of model years (model year 2020–2021) from regulatory and manufacturer-operated platforms. Both types of OBM platform followed the same data collection and transmission requirements as in the China VI emission standard[39,40] but were pre-processed into different forms. The OBM data from the governmental platforms were processed into daily information on the driving distance and fuel consumption, whereas the OBM data from the manufacturer-operated platforms provided original high-frequency (1 Hz or 0.1 Hz) records of operating conditions and fuel consumption. Supplementary Table 6 provides examples of OBM data from the governmental and manufacturer-operated platforms. We combined the two sources of DT data to analyse the usage pattern and fuel consumption of DTs (see Supplementary Note 1). In line with the categorization of ETs, we grouped the DT samples on the basis of GVW and utility (see Supplementary Table 5).

Calculation of real-world energy consumption and the usable battery range

Supplementary Note 1 explains the calculation procedure from the original records to the fleet-averaged results. For ETs, the trip-level electricity consumption of each ET is calculated based on the change in the SOC, the battery capacity and the driving distance for a single trip (equation (1)), which is further aggregated to the vehicle-level and fleet-level electricity consumption results (equation (2)):

$$\mathrm{EC}_{\mathrm{ET},k} = \frac{100 \times \mathrm{BatteryCapacity}_k \times \sum_{i=1}^{\mathrm{TripNum}_k} \Delta\mathrm{SOC}}{\sum_{i=1}^{\mathrm{TripNum}_k} L_i} \tag{1}$$

$$\mathrm{EC}_{\mathrm{ET\ fleet},m} = \frac{\sum_{k=1}^{\mathrm{VehicleNum}_{\mathrm{ET\ fleet},m}} \mathrm{EC}_{\mathrm{ET},k}}{\mathrm{VehicleNum}_{\mathrm{ET\ fleet},m}} \tag{2}$$

where $\mathrm{EC}_{\mathrm{ET},k}$, $\mathrm{BatteryCapacity}_k$ and $\mathrm{TripNum}_k$ denote the vehicle-average electricity consumption (kWh per 100 km), battery capacity (kWh) and total trip number of ET k, respectively, ΔSOC is the percentage change in SOC for a single trip made by ET k, and L_i is the distance of trip i (km). $\mathrm{EC}_{\mathrm{ET\ fleet},m}$ and $\mathrm{VehicleNum}_{\mathrm{ET\ fleet},m}$ are the average electricity consumption (kWh per 100 km) and the number of vehicles in electric fleet m, respectively.

The UBRs of ETs by vehicle and by fleet are calculated using equations (3) and (4), respectively:

$$\mathrm{UBR}_{\mathrm{ET},k} = \frac{100 \times \rho \times \mathrm{BatteryCapacity}_k}{\mathrm{EC}_{\mathrm{ET},k}} \tag{3}$$

$$\mathrm{UBR}_{\mathrm{ET\ fleet},m} = \frac{\sum_{k=1}^{\mathrm{VehicleNum}_{\mathrm{ET\ fleet},m}} \mathrm{UBR}_{\mathrm{ET},k}}{\mathrm{VehicleNum}_{\mathrm{ET\ fleet},m}} \tag{4}$$

where $\mathrm{UBR}_{\mathrm{ET},k}$ is the usable battery range (km) of ET k and ρ is the maximum SOC change for a fully charged battery, which we use 90% (the SOC from 95 to 5%) in this research. $\mathrm{UBR}_{\mathrm{ET\ fleet},m}$ is the usable battery range (km) of electric fleet m.

For diesel fleets, OBM data from the manufacturer-operated platforms were used to calculate the real-world fuel consumption of the vehicles (equation (5)) and fleets (equation (6)):

$$\mathrm{FC}_{\mathrm{DT},k} = \frac{100 \times \sum_{i=1}^{T_k} \mathrm{FuelRate}_{\mathrm{DT},k,i}}{\sum_{i=1}^{T_k} v_{\mathrm{DT},k,i}} \tag{5}$$

$$\mathrm{FC}_{\mathrm{DT\ fleet},m} = \frac{\sum_{k=1}^{\mathrm{VehicleNum}_{\mathrm{DT\ fleet},m}} \mathrm{FC}_{\mathrm{DT},k}}{\mathrm{VehicleNum}_{\mathrm{DT\ fleet},m}} \tag{6}$$

where $\mathrm{FC}_{\mathrm{DT},k}$, $\mathrm{FuelRate}_{\mathrm{DT},k,i}$, $v_{\mathrm{DT},k,i}$ and T_k denote the vehicle-average fuel consumption (l per 100 km), the instant fuel rate (l h^{-1}), instant speed (km h^{-1}) and total recorded time (s) of DT k, respectively. $\mathrm{FC}_{\mathrm{DT\ fleet},m}$ and $\mathrm{VehicleNum}_{\mathrm{DT\ fleet},m}$ are, respectively, the average fuel consumption (l per 100 km) and the number of vehicles in diesel fleet m. Supplementary Figure 4 shows the real-world fuel consumption values of the different DT fleets.

Life-cycle CO_2 emissions calculation

Life-cycle CO_2 emissions are composed of WTW and vehicle-cycle results. We used the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation (GREET) model[41] with China-specific inputs[30,42] to evaluate the life-cycle CO_2 emissions of each fleet in China at the categorical level. Life-cycle CO_2 emissions of ETs and DTs were evaluated as equations (7) and (8) separately:

$$\mathrm{CO}_{2\,\mathrm{life\text{-}cycle,ET}_m} = \frac{1,000 \times \mathrm{CO}_{2\,\mathrm{vehicle\text{-}cycle,ET}_m}}{\mathrm{a} \times \mathrm{VKT}_m} + \mathrm{CO}_{2\,\mathrm{WTW,ET}_m} \tag{7}$$

where $\mathrm{CO}_{2\,\mathrm{life\text{-}cycle,ET}_m}$ denotes the life-cycle CO_2 emissions (g km^{-1}) of an individual ET in fleet m, $\mathrm{CO}_{2\,\mathrm{vehicle\text{-}cycle,ET}_m}$ denotes the vehicle-cycle CO_2 emissions (kg) of an individual ET in fleet m, a is the lifespan of the ETs (set to ten years), VKT_m is the average yearly vehicle mileage (km y^{-1}) of electric fleet m and $\mathrm{CO}_{2\,\mathrm{WTW,ET}_m}$ is the WTW CO_2 emissions (g km^{-1}) of an individual ET in fleet m.

For the DTs, we have:

$$\mathrm{CO}_{2\,\mathrm{life\text{-}cycle,DT}_m} = \frac{1,000 \times \mathrm{CO}_{2\,\mathrm{vehicle\text{-}cycle,DT}_m}}{\mathrm{a} \times \mathrm{VKT}_m} + \mathrm{CO}_{2\,\mathrm{WTW,DT}_m} \tag{8}$$

where $\mathrm{CO}_{2\,\mathrm{life\text{-}cycle,DT}_m}$ is the life-cycle CO_2 emissions (g km^{-1}) of an individual DT in fleet m, $\mathrm{CO}_{2\,\mathrm{vehicle\text{-}cycle,DT}_m}$ is vehicle-cycle CO_2 emissions (kg) of an individual DT in fleet m, a is the lifespan of DTs (also set to ten years), VKT_m is the average yearly vehicle mileage (km y^{-1}) of diesel fleet m and $\mathrm{CO}_{2\,\mathrm{WTW,DT}_m}$ is the WTW CO_2 emissions (g km^{-1}) of an individual DT in fleet m. See Supplementary Table 7 and the Data availability statement for detailed life-cycle CO_2 emission results.

For the ETs, the WTW CO_2 emissions were evaluated on the basis of the GREET model[41] with China-specific inputs[30]. We used the fleet-average electricity consumption (equation (9)) as input for the evaluation:

$$\mathrm{CO}_{2\,\mathrm{WTW,ET}_m} = \frac{\mathrm{EC}_{\mathrm{ET\ fleet},m} \times \mathrm{EF}_{\mathrm{electricity,CO_2}}}{100 \times \eta} \tag{9}$$

where $\mathrm{EC}_{\mathrm{ET\ fleet},m}$ is the electricity consumption (kWh per 100 km) of fleet m and $\mathrm{EF}_{\mathrm{electricity,CO_2}}$ is the CO_2 emission factor (g kWh^{-1}) of electricity generation[30]. For the baseline, we used the national averaged gradient emission factor for the lifespan (2020–2030), that is, 481 g kWh^{-1} (Supplementary Table 8). η is the charging efficiency, 85%.

For the diesel fleets, the WTW CO_2 emissions were evaluated based on fuel consumption results using equation (10):

$$\mathrm{CO}_{2\,\mathrm{WTW,DT}_m} = 10 \times \mathrm{FC}_{\mathrm{DT\ fleet},m} \times \mathrm{EF}_{\mathrm{diesel,CO_2}} \tag{10}$$

https://doi.org/10.1038/s41560-024-01602-x

where $FC_{DT\,fleet,m}$ is the real-world fuel consumption (l per 100 km) of fleet m and EF_{diesel,CO_2} is the comprehensive CO_2 emission factor for diesel, for which we used 3.15 kg l^{-1} in this research. We considered a 15% fuel consumption reduction for diesel fleets in 2030, referring to the fuel consumption limits for commercial vehicles in China[41,43]. However, we did not consider the possible vehicle weight change in the future and its corresponding influence in this research.

The vehicle cycle estimates the CO_2 emissions from the production of vehicle materials (excluding batteries for ETs), battery production for ETs, vehicle fluids and vehicle assembly[30,41,42]. For each fleet, we used the median kerb vehicle weight and battery weight to represent the ET category (see Supplementary Table 7), on the basis of which we attributed the material weights by ratio from representative vehicles of different fleets. Vehicle-cycle CO_2 emissions were evaluated using equation (11):

$$CO_{2\,\text{vehicle-cycle,fleet}_m} = \sum w_{i,m} \times CO_{2\,\text{material}_i} \quad (11)$$

where $CO_{2\,\text{vehicle-cycle,fleet}_m}$ is vehicle-cycle CO_2 emissions (kg) of an individual vehicle in fleet m, $w_{i,m}$ is the weight (kg) of material i of the representative vehicle in fleet m and $CO_{2\,\text{material}_i}$ is the carbon intensity ($kgCO_2\,kg^{-1}$) for the production of material i (refs. 30,41,42), which is provided in Data availability statement.

Total cost of ownership

The TCO analysis scoped in China and included five components: (1) the purchase cost, which included the vehicle purchase price, purchase tax and subsidies; (2) the fuel cost; (3) insurance, tax and other fees, such as road tolls, compulsory liability insurance for vehicle traffic accidents and annual usage tax; (4) maintenance and repair costs; and (5) the residual value, which is zero for a lifespan longer than nine years (ref. 10). In Fig. 2b and Supplementary Fig. 6b, components (3)–(5) were aggregated as 'other cost'. Details of these components are given in Supplementary Note 2. Notably, because of the high sensitivity of truck purchase prices, we could get only the average price of the top five/top ten models for each category, so currently the TCO model is category-specific but not vehicle model-specific.

We evaluated the category-specific TCO of ETs using equation (12):

$$\text{TCO}_{\text{individual,ET}_m} = \frac{\text{PurCost}_{\text{ET}_m} + \left(\text{ChgCost}_{\text{ET}_m} + \text{ITF}_{\text{ET}_m} + \text{M\&R}_{\text{ET}_m}\right) \times \frac{1-(1-r)^a}{r} - \text{Res}_{a,m}}{a \times \text{VKT}_{\text{ET}_m}} \quad (12)$$

where $\text{PurCost}_{\text{ET}_m}$ and $\text{ChgCost}_{\text{ET}_m}$ are the fleet-averaged purchase cost and charging cost (USD) of electric fleet m, respectively, which are evaluated using Supplementary Equation (2) (see Supplementary Note 2) and equation (13), respectively; ITF_{ET_m} is a term that represents the insurance, taxes, and fees (USD) of electric fleet m, calculated using Supplementary Equation (4); $\text{M\&R}_{\text{ET}_m}$ is the maintenance and repair cost (USD) of electric fleet m, calculated using Supplementary Equation (6); a is the vehicle lifespan, which is set to ten years in the baseline scenario; $\text{Res}_{a,m}$ is the average residual value (USD) after lifespan a, evaluated using Supplementary Equation (8); r is the discount rate, which is 0.05; and VKT_{ET_m} is the average yearly mileage (km) of fleet m.

$$\text{ChgCost}_{\text{ET}_m} = \frac{\sum_{k=1}^{\text{VehicleNum}_{\text{ET fleet},m}} \sum_{n=1}^{\text{ChgNum}_{\text{ET},k}} \text{Chg}_{k,n} \times \left(\overline{\text{EP}_{h_{st},h_{ed},\text{loc}}} + I_{k,n} \times F_{\text{service,loc}}\right)}{\text{VehicleNum}_{\text{ET fleet},m}} \quad (13)$$

where $\text{VehicleNum}_{\text{ET fleet},m}$ is the total number of vehicles in ET fleet m; $\text{ChgNum}_{\text{ET},k}$ is the number of charging events of vehicle k in fleet m; $\text{Chg}_{k,n}$ is the charging electricity volume (kWh) of vehicle k in charging event n; $\overline{\text{EP}_{h_{\text{st},m},h_{\text{ed},m},\text{loc}}}$ is the average electricity price (USD kWh^{-1}) within the charging hours from $h_{\text{st},m}$ (start hour of charging event n) to $h_{\text{ed},m}$ (end hour of charging event n) in region loc (vehicle registration place); $I_{k,n}$ is a dummy variable used to identify fast charging events, which is set to equal to 1 for fast charging and 0 for slow charging; and $F_{\text{service,loc}}$ is the service fee (USD) of region loc.

The category-specific TCO of DTs was evaluated using equation (14):

$$\text{TCO}_{\text{individual,DT}_m} = \frac{\text{PurCost}_{\text{DT}_m} + \left(\text{FuelCost}_{\text{DT}_m} + \text{ITF}_{\text{DT}_m} + \text{M\&R}_{\text{DT}_m}\right) \times \frac{1-(1-r)^a}{r} - \text{Res}_{a,m}}{a \times \text{VKT}_{\text{DT}_m}} \quad (14)$$

where $\text{PurCost}_{\text{DT}_m}$ and $\text{FuelCost}_{\text{DT}_m}$ are the fleet-averaged purchase cost and fuel cost (USD) of diesel fleet m, respectively, which are evaluated using Supplementary Equation (3) (see Supplementary Note 2) and equation (15), respectively; ITF_{DT_m} is a term representing the insurance, taxes and fees (USD) of diesel fleet m, calculated using Supplementary Equation (5); $\text{M\&R}_{\text{DT}_m}$ is the maintenance and repair cost (USD) of diesel fleet m, calculated using Supplementary Equation (7); a is the vehicle lifespan, again set to ten years in the baseline scenario; $\text{Res}_{a,m}$ is the average residual value after lifespan a, and 0 is used for the baseline scenario ($a = 10$); r is the discount rate, also set to 0.05; and VKT_{DT_m} is the average yearly mileage (km) of diesel fleet m.

$$\text{FuelCost}_{\text{DT}_m} = \frac{1}{100} \times \text{DieselPrice} \times \text{VKT}_{\text{DT}_m} \times \text{FC}_{\text{DT}_m} \quad (15)$$

where DieselPrice is the diesel market price (USD $l^{-}1$) and $FC_{DT,m}$ is the average fuel consumption (L per 100 km) of diesel fleet m. In future scenarios, a 15% improvement in fuel economy is considered for diesel fleets.

Priority group identification and relevant effects

We identified vehicles in the priority group according to their daily mileages. We defined the priority group mileage when, at this daily mileage, the ratio of ETs who had a higher average daily mileage (shaded in darker green in Fig. 1b) is equivalent to the ratios of DTs who had lower average daily mileage (shaded in darker red under the red curve in Fig. 1b) in the respective truck category. At the priority group mileage, the ratio of ETs who have a higher average daily mileage (or the ratios of DTs who have lower average daily mileage) is the priority group ratio. We calculated the priority group life-cycle CO_2 and TCO values using equations (7)–(11) and (12)–(15), respectively, in the basis of energy consumption values and vehicle mileages derived from vehicles in the priority group.

Replacement rate simulation to match the fleet-level work demand

We extracted detailed DT trip chains from the OBM data, which included the trip mileage, average speed and parking time. For each fleet, we assumed that ETs with a representative battery capacity (the median of the capacities for current models in the category) drive the same mileage at the same average speed for each trip chain as DT, and are charged during the parking time via fast charging (60 kW)[28].

During modelling of the replacement rate, we normalized the payload (shown in Supplementary Fig. 14), mileage (as trip chains from DTs) and truck operational speed (as average speed of DT for each trip) of the ETs. We assumed that the ETs can be charged using 60 kW infrastructures at every parking period between two consecutive trip chains. For a specific DT trip, we assumed that the ET must run at the same speed as a DT, and estimated the corresponding electricity consumption from the speed–electricity consumption relationship derived from Supplementary Fig. 3b. Under the current usage scenario, we assumed that ETs keep current battery usage patterns as shown in Supplementary Table 9—for example, an electric LD delivery truck can use 41% of its SOC as a maximum for each trip. With the optimized usage scenario, we assumed an average battery usage of 85% SOC for the ETs.

https://doi.org/10.1038/s41560-024-01602-x

We estimated the number of ETs needed on average to complete all of the trip chains from one DT in one day, and derived the replacement rate by multiplying this number by the payload ratio (derived from Supplementary Fig. 14), as in equation (16):

$$\mathrm{rr}_m = \frac{N_{\mathrm{ET}_m}}{N_{\mathrm{DT}_m}} \times \mathrm{Pl}_m \tag{16}$$

where rr_m is the replacement rate of truck fleet m, N_{ET_m} is the total number of ETs needed to complete all of the DT daily trip chains under the current/optimized battery usage, N_{DT_m} is the total number of DTs providing the daily trip chains and Pl_m is the ratio of the average DT payload versus the average ET payload for fleet m. Detailed replacement rate results are shown in Supplementary Table 2b.

Then, the fleet-level TCO and life-cycle CO_2 of ETs after usage normalization were estimated using equations (17) and (18), respectively:

$$\mathrm{TCO}_{\mathrm{fleet,ET}_m} = \mathrm{rr}_m \times \mathrm{TCO}_{\mathrm{individual,ET}_m} \tag{17}$$

where $\mathrm{TCO}_{\mathrm{fleet,ET}_m}$ is the fleet-level TCO (USD per km) of ETs after usage normalization and $\mathrm{TCO}_{\mathrm{individual,ET}_m}$ is the category-specific TCO (USD per km) of individual ETs in fleet m.

$$\mathrm{CO}_{2\,\mathrm{fleet,ET}_m} = \mathrm{rr}_m \times \frac{1{,}000 \times \mathrm{CO}_{2\,\mathrm{vehicle\text{-}cycle,ET}_m}}{a \times \mathrm{VKT}_m} + \mathrm{CO}_{2\,\mathrm{WTW,ET}_m} \tag{18}$$

where $\mathrm{CO}_{2\,\mathrm{fleet,ET}_m}$ is the fleet-level life-cycle CO_2 (g km^{-1}) of ET fleet m after usage normalization and $\mathrm{CO}_{2\,\mathrm{vehicle\text{-}cycle,ET}_m}$ is the category-specific vehicle-cycle CO_2 emissions (kg) of individual ETs in fleet m; a is the lifespan of the ETs, set to ten years as earlier; VKT_m is the average yearly vehicle mileage (km y^{-1}) of electric fleet m; and $\mathrm{CO}_{2\,\mathrm{WTW,ET}_m}$ is the category-specific WTW CO_2 emissions (g km^{-1}) of individual ET in fleet m.

If vehicle usage is increased, the simulated replacement rate will decrease. We quantified the usage intensity increase via the ratio of the baseline (without optimization) replacement rate and the optimized replacement rate using equation (19):

$$\mathrm{UsageInc}_{\mathrm{ET}_m} = \frac{\mathrm{rr}_{m,\mathrm{baseline}}}{\mathrm{rr}_{m,\mathrm{opt}}} \tag{19}$$

where $\mathrm{UsageInc}_{\mathrm{ET}_m}$ is the fleet-level usage increase rate of ET fleet m, and $\mathrm{rr}_{m,\mathrm{baseline}}$ and $\mathrm{rr}_{m,\mathrm{opt}}$ are, respectively, the replacement rates at the baseline scenario (with current usage) and the optimized usage scenario. We then used the usage increase rate to adjust the VKT_m (annual mileage) and $\mathrm{ChgCost}_{\mathrm{ET}_m}$ (charging cost), re-evaluating the life-cycle CO_2 emissions (using equation (7)) and TCO values (using equations (12) and (13)) of individual ETs under the optimized usage.

Future scenario design

We designed several future scenarios, as shown in Fig. 4 and Supplementary Fig. 9. All future scenarios are based on the optimized usage of ETs (that is, an average battery use of 85% SOC), and include a 15% fuel consumption reduction for DTs, as required by the commercial vehicle fuel consumption standard in China[41]. The future scenarios are listed as follows:

Current optimized scenario + fast charging (60 kW). The current scenario in which ETs use 60 kW fast charging[28].

BS increase + fast charging (60 kW). A 50% increase in battery capacity (with unchanged battery energy density and unit cost) and ETs use 60 kW fast charging.

ED increase + fast charging (60 kW). The average pack-level energy density of batteries is increased to 220 Wh kg^{-1}, and battery weights are kept the same with current ET models. At the same time, the battery pack cost is reduced from US\$0.16 to 0.085 per watt-hour. ETs use 60 kW fast charging.

EC reduction + fast charging (60 kW). The electricity consumption of ETs is decreased by 25% compared with the current fleet-averaged electricity consumption[22,44,45]. ETs use 60 kW fast charging.

CE + fast charging (60 kW). Sustainable electricity deployed in 2030–2040 (see Supplementary Table 7 for CO_2 intensity of electricity generation). ETs use 60 kW fast charging.

CE + ED increase + fast charging (60 kW). The pack-level energy density of batteries is increased to 220 Wh kg^{-1} (with an unchanged battery weight). The battery pack cost is reduced from US\$0.16 to 0.085 per watt-hour. Sustainable electricity deployed in 2030–2040, and ETs use 60 kW fast charging.

CE + ED increase + battery swapping. The pack-level energy density of batteries is increased to 220 Wh kg^{-1} (with an unchanged battery weight). The battery pack cost is reduced from US\$0.16 to 0.085 per watt-hour. Sustainable electricity deployed in 2030–2040 with battery swapping for ETs.

CE + ED increase + supercharging (350 kW). The pack-level energy density of batteries is increased to 220 Wh kg^{-1} (with an unchanged battery weight). The battery pack cost reduced from US\$0.16 to 0.085 per watt-hour. Sustainable electricity deployed in 2030–2040, and ETs use 350 kW Level 3 charging.

CE + BS increase + ED increase + EC reduction + battery swapping. The pack-level energy density of batteries is increased to 220 Wh kg^{-1} (with an unchanged battery weight) and with a 50% increase in battery capacity. The battery pack cost is reduced from US\$0.16 to 0.085 per watt-hour. Electricity consumption of the ETs is decreased by 25% compared with the current fleet-averaged electricity consumption. Sustainable electricity deployed in 2030–2040, with battery swapping for ETs.

Calculation of fleet-level electrification effects with battery swapping

To evaluate the number of additional swapped batteries, we calculated the daily energy demand using equation (20):

$$\mathrm{EnergyDemand}_{\mathrm{DT},m} = \frac{0.2778}{100} \times Q_{\mathrm{diesel}} \times \overline{\mathrm{FC}}_{\mathrm{DT},m} \times \bar{L}_{\mathrm{DT},m} \tag{20}$$

where $\mathrm{EnergyDemand}_{\mathrm{DT},m}$ is the average daily energy demand (kWh) of diesel fleet m, Q_{diesel} is the calorific value of diesel, which is 35.7 MJ l^{-1}, $\overline{\mathrm{FC}}_{\mathrm{DT},m}$ is the same as defined in equation (15) and $\bar{L}_{\mathrm{DT},m}$ is the average daily mileage (km) of diesel fleet m. The number of additional batteries needed for swapping ($N_{\mathrm{battery},m}$) is then calculated using equation (21):

$$N_{\mathrm{battery},m} = \max\left(\frac{\mathrm{EnergyDemand}_{\mathrm{DT},m}}{\overline{\mathrm{BatteryCapacity}}_{\mathrm{ET},m} \times \rho_{\mathrm{opt}}} \times \mathrm{Pl}_m - 1, 0\right) \tag{21}$$

where $\overline{\mathrm{BatteryCapacity}}_{\mathrm{ET},m}$ is the average battery capacity (kWh) of ET fleet m and ρ_{opt} is the optimized battery usage ratio (at 85%)—see Supplementary Table 3 for detailed results of the number of additional batteries needed under the optimized usage scenarios.

Then fleet-level TCO and life-cycle CO_2 of ETs after usage normalization with battery swapping were estimated using equations (22) and (23), respectively:

$$\mathrm{TCO}_{\mathrm{fleet,ET}_m,\mathrm{bw}} = \mathrm{TCO}_{\mathrm{individual,ET}_m} + N_{\mathrm{battery},m} \times \mathrm{TCO}_{\mathrm{battery}_m} \tag{22}$$

where $\mathrm{TCO}_{\mathrm{fleet,ET}_m,\mathrm{bw}}$ is the fleet-level TCO (USD per km) of ET fleet m after usage normalization with battery swapping and $\mathrm{TCO}_{\mathrm{battery}_m}$ is the category-specific TCO (USD per km) of one additional battery for fleet m.

$$\mathrm{CO}_{2\,\mathrm{fleet,ET}_m,\mathrm{bw}} = N_{\mathrm{battery},m} \times \mathrm{CO}_{2\,\mathrm{battery}_m} + \mathrm{CO}_{2\,\mathrm{life\text{-}cycle,ET}_m} \tag{23}$$

where $\mathrm{CO}_{2\,\mathrm{fleet,ET}_m,\mathrm{bw}}$ is the fleet-level life-cycle CO_2 (g km^{-1}) of fleet m after usage normalization with battery swapping, $\mathrm{CO}_{2\,\mathrm{battery}_m}$ is the category-specific vehicle-cycle CO_2 emissions (g km^{-1}) of one additional battery for fleet m and $CO_{2\,\text{life-cycle},ET_m}$ is the category-specific life-cycle CO_2 emissions (g km^{-1}) of individual ETs in fleet m.

Calculation of cost/CO_2 break-even replacement rate

The cost and CO_2 break-even replacement rate are estimated as equations (24) and (25) separately:

$$rr_{\text{TCO breakeven}} = \frac{TCO_{DT_m}}{TCO_{ET_m}} \quad (24)$$

where $rr_{\text{TCO breakeven}}$ is the replacement rate at which ETs can reach a TCO balance with their diesel counterparts, and TCO_{DT_m} and TCO_{ET_m} are the category-specific TCO values (g km^{-1}) of diesel and electric vehicles in fleet m, respectively.

$$rr_{CO_2\,\text{breakeven}} = \frac{CO_{2\,WTW,DT_m} - CO_{2\,WTW,ET_m}}{\frac{1{,}000\times CO_{2\,\text{vehicle-cycle},ET_m}}{a\times VKT_{ET_m}} - \frac{1{,}000\times CO_{2\,\text{vehicle-cycle},DT_m}}{a\times VKT_{DT_m}}} \quad (25)$$

where $rr_{CO_2\,\text{breakeven}}$ is the replacement rate at which ETs can reach a life-cycle CO_2 balance with their diesel counterparts, $CO_{2\,WTW,DT_m}$ and $CO_{2\,WTW,ET_m}$ are the category-specific WTW CO_2 emissions (g km^{-1}) of individual vehicles in diesel and electric fleet m, respectively, and $CO_{2\,\text{vehicle-cycle},ET_m}$ and $CO_{2\,\text{vehicle-cycle},DT_m}$ are the category-specific vehicle-cycle CO_2 emissions (kg) of individual vehicles in diesel fleet and electric fleet m, respectively.

Data availability

Material CO_2 emission factors in China, life-cycle CO_2 emission data and TCO results are available via Figshare at https://doi.org/10.6084/m9.figshare.24421210 (ref. 46). More specific datasets or materials are available from S.Z. or Y.W. upon reasonable request. Source data are provided with this paper.

Code availability

The codes that support the findings of this study are available from the corresponding authors upon reasonable request.

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Acknowledgements

We are grateful to the National Key Research and Development Program of China (Grant No. 2022YFC3703600, Y.W.), the National Natural Science Foundation of China (52170111, S.Z.) and Energy Foundation China (Grant No. G-2310-35151, S.Z.). We thank M. Wang from Argonne National Laboratory for useful discussion. We thank A. Wang and all members from MIT Senseable City Lab for their generous help. We thank the North American Council for Freight Efficiency (NACFE) for the data and visualized results for the Run on Less – Electric Depot program.

Author contributions

P.Z., S.Z., P.S., C.R., Z.W. and Y.W. designed the research; D.C., P.L., Z.Z., J.L. and Z.W. prepared and pre-processed the data; P.Z., S.Z. and P.S. developed the assessment methods and performed the research; P.Z., S.Z., P.S. and Y.W. analysed the data; P.S., F.W., C.R. and Y.W. provided valuable discussions and edited the manuscript; P.Z., S.Z., P.S., C.R. and Y.W. wrote and revised the paper.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41560-024-01602-x.

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Peer review information *Nature Energy* thanks Kelly Fleming, Felipe Rodriguez and the other, anonymous, reviewer(s) for their contribution to the peer review of this work