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Real-world performance of battery electric heavy-duty vehicles in China

ENERGY CONSUMPTION, RANGE, AND CHARGING PATTERNS

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INTRODUCTION

Because of their significant potential to reduce greenhouse gas emissions, battery electric heavy-duty vehicles (HDVs) are expected to play an important role in helping to deliver on China's national decarbonization commitment, which is carbon peaking by 2030 and carbon neutrality by 2060.[1] Indeed, electric buses already dominate new bus sales in China, and sales in 2021 were over 90% of the entire global market for electric buses.[2] The electric truck market, meanwhile, is still in an infant stage. Approximately 25,000 electric trucks were sold in China in 2022, 5% of the overall truck market.[3]

Figure 1 illustrates sales of battery electric HDVs in China over the past decade. There were generous financial incentives from the national government beginning in 2013, and the market grew rapidly until 2016. The national government subsequently reduced direct financial support, and from 2017 to 2020 there was a decline in sales. However, the market rebounded in 2021 due to quick adoption of battery-swapping trucks and electric bus procurement demands from cities.[4]

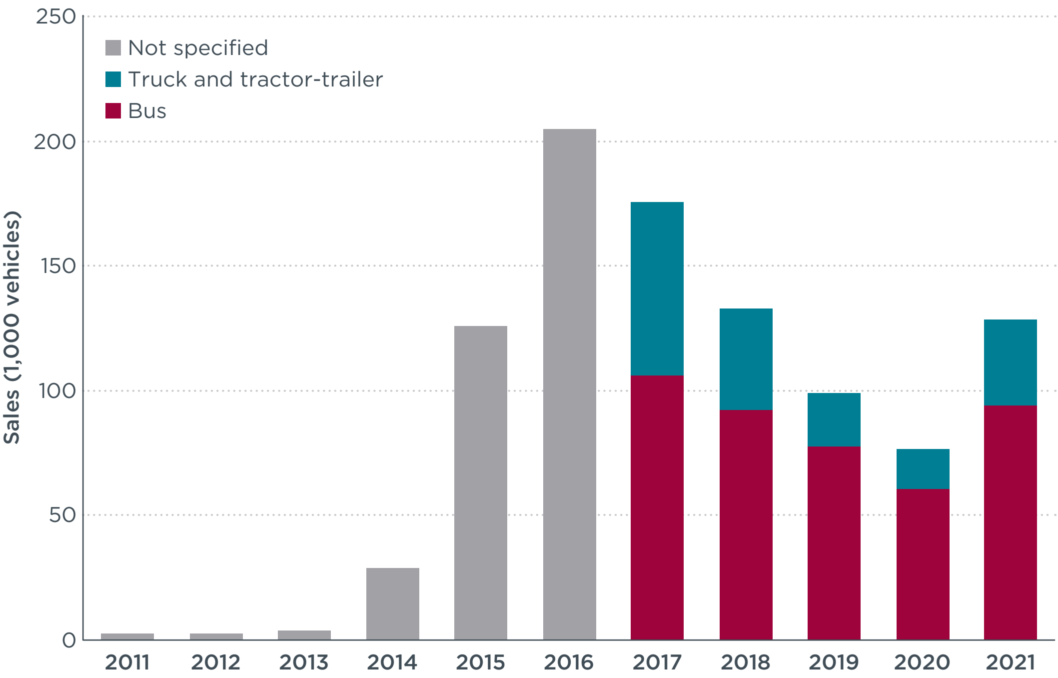

Figure 1. Sales of electric buses, trucks, and tractor-trailers in China from 2011 to 2021.

According to vehicle type-approval documents, which are maintained by the Ministry of Industry and Information Technology (MIIT) of China, the average nominal range for electric trucks was 320 km in 2021. However, as this study shows, in real-world cases, electric trucks are much more commonly used in short-distance deliveries of less than 200 km.

The objective of this report is to offer a range of stakeholders, including consumers, businesses, governments, and researchers, analysis of the real-world performance and use pattern of battery electric HDVs based on a large set of real-world data. The data used in this study was acquired from the open lab of the National Big Data

1 Yao Wang et al., "Carbon Peak and Carbon Neutrality in China: Goals, Implementation Path, and Prospects," *China Geology* 4, (2021): 720–746. https://doi.org/10.31035/cg2021083

2 Hongyang Cui and Dale Hall, "Annual Update on the Global Transition to Electric Vehicles: 2021," (ICCT: Washington, DC, 2022), https://theicct.org/wp-content/uploads/2022/06/global-ev-update-2021-jun22.pdf .

3 Xinchi Yin et al., "汽车行业电动重卡行业专题：电动重卡方兴未艾 加速渗透奇点已至," *Sina Finance*, (2023). https://stock.finance.sina.com.cn/stock/go.php/vReport_Show/kind/search/rptid/729724512698/index.phtml

4 Shiyue Mao et al., "Zero-Emission Bus and Truck Market in China: A 2021 Update," (ICCT: Washington, DC, 2023), https://theicct.org/publication/china-hvs-ze-bus-truck-market-2021-jan23/

Alliance of New Energy Vehicles (NDANEV), an organization founded in 2017 that aims to better monitor and manage new energy vehicles (NEVs). NEVs, including battery electric, plug-in hybrid electric, and fuel-cell electric vehicles, have been required to be connected to the open lab of NDANEV since then. The total number of vehicles exceeded 9.2 million, 90% of China's NEV stock, and these vehicles had total mileage of over 300 billion kilometers by July 17, 2022.[5] Vehicles upload operational data every 30 seconds. The raw data includes vehicle status, speed, accumulated mileage, voltage, state of charge (SOC), temperature, and more.

Figure 2 illustrates the scheme of this project in terms of data management and sharing. Due to regulations regarding data management and privacy, ICCT accessed only the aggregated data from NDANEV by identifying the scope, metrics, and methodology of our intended work. ICCT has not independently verified the data because we do not have access to the raw data.

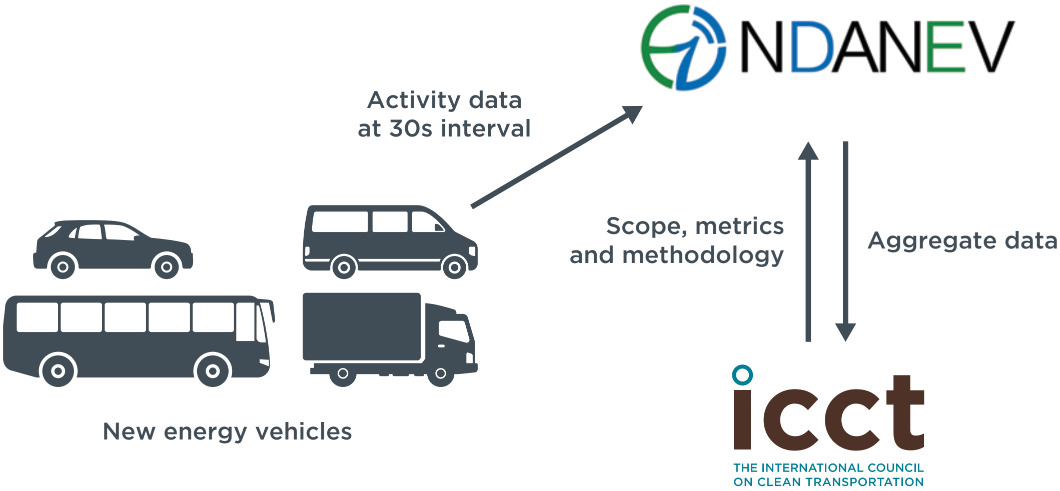

Figure 2. Data and workflow between ICCT and the open lab of NDANEV for this analysis.

5 Sina Finance, "9.27 Million New Energy Vehicles Have Been Connected to the Open Lab of NDANEV, Accounting for 90% of Stock," July 19, 2022, https://finance.sina.com.cn/jjxw/2022-07-19/doc-imizmscv2502545.shtml?cref=cj

SCOPE AND METHODS

We evaluated the best-selling vehicle model in 2021 in each of nine popular categories of electric HDVs: city bus, coach, tractor-trailer, dump truck, straight truck, stake truck, box truck, special use vehicle, and tank truck. For the model that was number one in sales nationally in each of the nine vehicle categories, the top three best-selling cities in 2021 were identified, and, collectively, that yielded 11,993 vehicles in the data sample. Vehicle activity data from full calendar year 2021 was collected and summarized. Table 1 details the data sample by category.

Table 1. Details of the models selected for analysis

Categories	Tractor-trailer	City bus	Coach	Dump truck	Straight truck	Stake truck	Special use vehicle	Tank truck	Box truck
Model year	2021	2021	2021	2021	2018	2020	2021	2021	2018
Sample size	387	3,645	471	174	246	218	301	367	6,184
Energy consumption (kWh/100km)	148.4	52.7	53.3	117.5	30.0	54.5	86.1	85.7	30.0
Nominal range (km)	190	385	285	360	240	345	365	255	240

The 18 cities shown in Figure 3 were among the top three best-selling cities for the models chosen, and they each have different climate and geographical conditions. Harbin is the provincial capital city of the northeast province Heilongjiang, which is known for its extreme cold climate with temperatures that sometimes drop to around -30 °C in winter. Bijie is a medium-size city located in Guizhou province, and it is known for its mountainous terrain and bumpy roads.

Figure 3. Cities from which vehicle data was assessed in this analysis.

To emphasize, this analysis only covers select models in certain cities. Performance in the real world is also affected by other factors such as topography, traffic, and driving patterns.

A list of the equations used to calculate the key real-world performance metrics from the different parameters in the event-level data is in the Appendix. Note that figures for both energy consumption and range are based on median values of the sample.

ENERGY CONSUMPTION

In this report, energy consumption is presented in kWh per 100 km, and we illustrate the energy consumption of electric HDVs under "cold" (<0 °C), "hot" (>30 °C), and "high-speed" (>76 km/h) conditions in Figure 4. The ambient temperature is daily average temperature rather than for each trip.

For most of the truck models, real-world energy consumption was higher than the nominal values. In both "cold" and "hot" conditions, the energy consumption of special-use vehicles was nearly 150% of the nominal values. Electric vehicles cannot warm cabins with heat from the engine the way combustion engine vehicles do, and because of that about 30% extra energy is typically required for heating.[6]

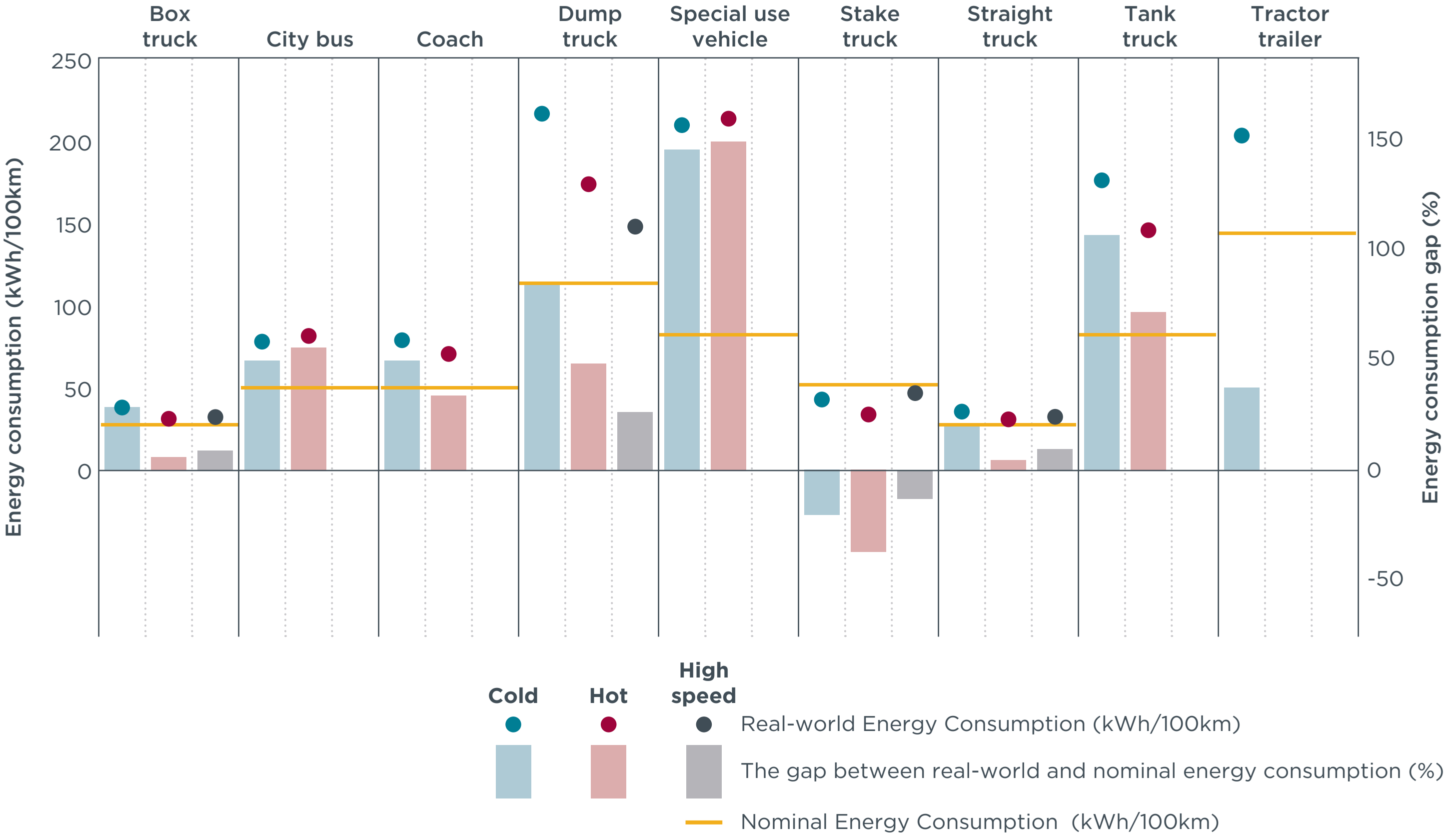

Figure 4. Median energy consumption and the gap to the nominal values for each vehicle category.

Note: Real-world driving data were missing for high-speed for special-use vehicles, tank trucks, and tractor-trailers, and "hot" values for tractor-trailers were also missing.

6 Chengguo Li et al., "Reducing Mobile Air Conditioner (MAC) Power Consumption Using Active Cabin-Air-Recirculation in A Plug-In Hybrid Electric Vehicle (PHEV)," World Electric Vehicle Journal 9, no. 4 (2018): 51. https://doi.org/10.3390/wevj9040051.

ELECTRIC RANGE

Figure 5 shows the electric ranges of each vehicle category in the selected cities; these are calculated values based on accumulated trips collected by the open lab. Note that this method introduces some uncertainties. For example, data might be unevenly distributed across working conditions. Additionally, numerical rounding errors could be introduced. The truck models in the sample appear suitable for operations under 300 km. Tractor-trailers are commonly used in long-haul transport of goods; in China, tractor-trailers averaged about 300 km per day in 2020, according to a survey.[7] The nominal range of the tractor-trailer model in this data set is 190 km, and we found real-world ranges of between about 130 km and 140 km. With that range, this model would be capable of medium-range driving and freight if it were recharged twice per day.

For each model, the difference between real-world and nominal range is nearly constant across the different cities, and the greatest variance between cities seems to be about 10%. This implies that climate and terrain conditions are less important for procurement decisions than gathering information about the vehicle's real-world performance and suggests that, as a general rule, a discount factor of 0.6 applied to the nominal value would help measure how far the to-be-procured model can travel most of time.

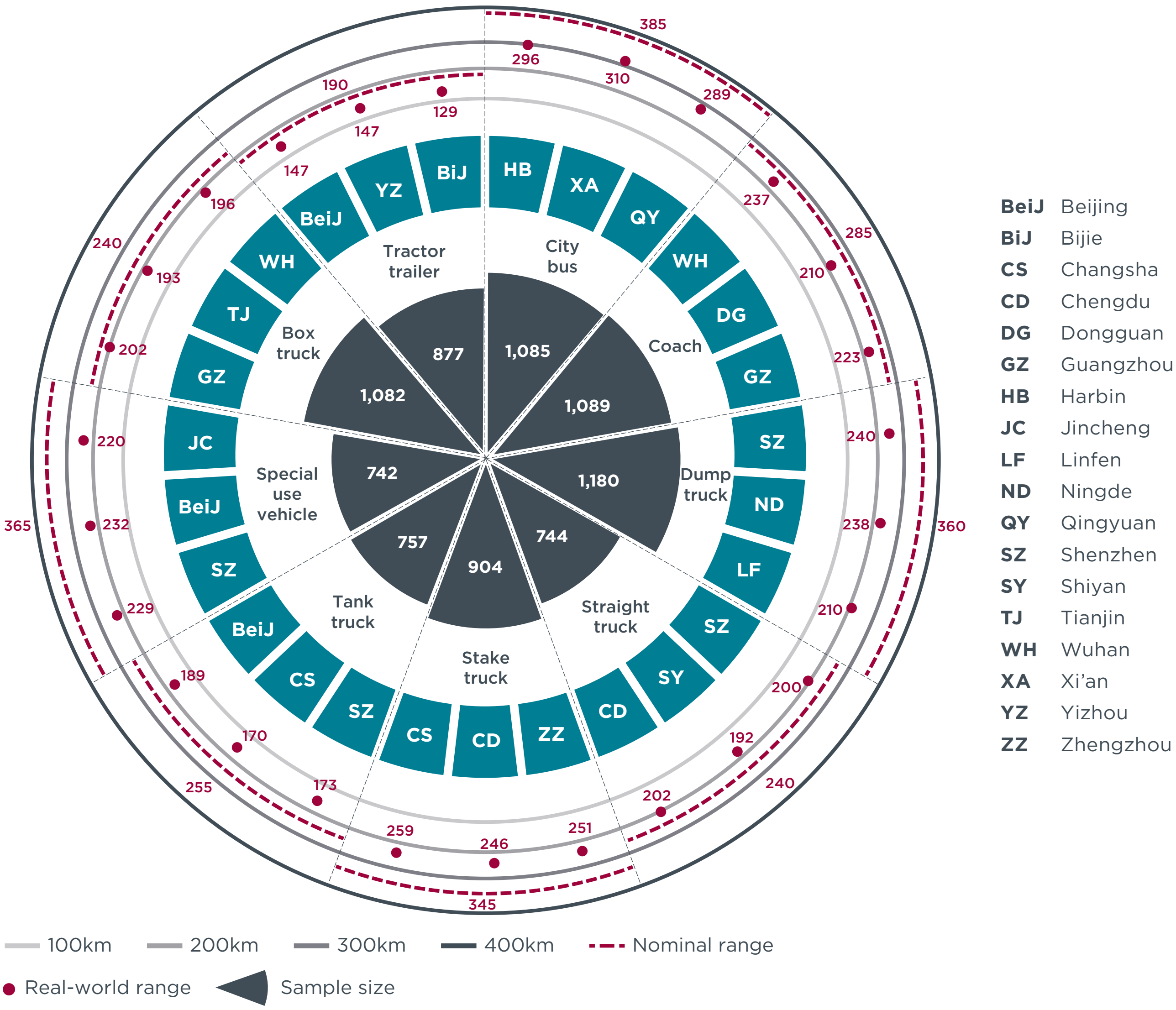

Figure 5. Calculated real-world ranges (median values) of the vehicle categories in selected cities.

7 Sinoiov and RIOH, "基于大数据的中国公路货运行业运行分析报告（2020）."2021, https://www.163.com/dy/article/GLSGJ67N05388W2A.html. (Chinese only)

CHARGING PATTERNS

Figure 6 illustrates the real-world charging rate and charging duration for the electric HDVs in daily operations. One of the key insights is that operators appear to be applying a strategy of "charging whenever possible" because there are frequent charging events with small state of charge (SOC) growth. 70% of charging activities happened within the range of 40%–60% SOC. The charging cases for 100% SOC fall on the **red** "0%–100% SOC charging curve" in the figure.

The average charging rate of electric HDVs in this project is approximately 0.4C and that implies that fast charging, which is normally over 1C, and ultra-fast charging, over 2C, technology is not yet fully available. Use of slower chargers means longer charging time. That would tend to increase the operating costs of the vehicle.

The charging pattern also likely reflects that owners and operators have some amount of range anxiety, as more frequent charging activities guarantee readiness for any ad-hoc activities. On the other hand, the charging pattern also suggests that batteries are not being efficiently utilized, which reduces the real-world efficiency.

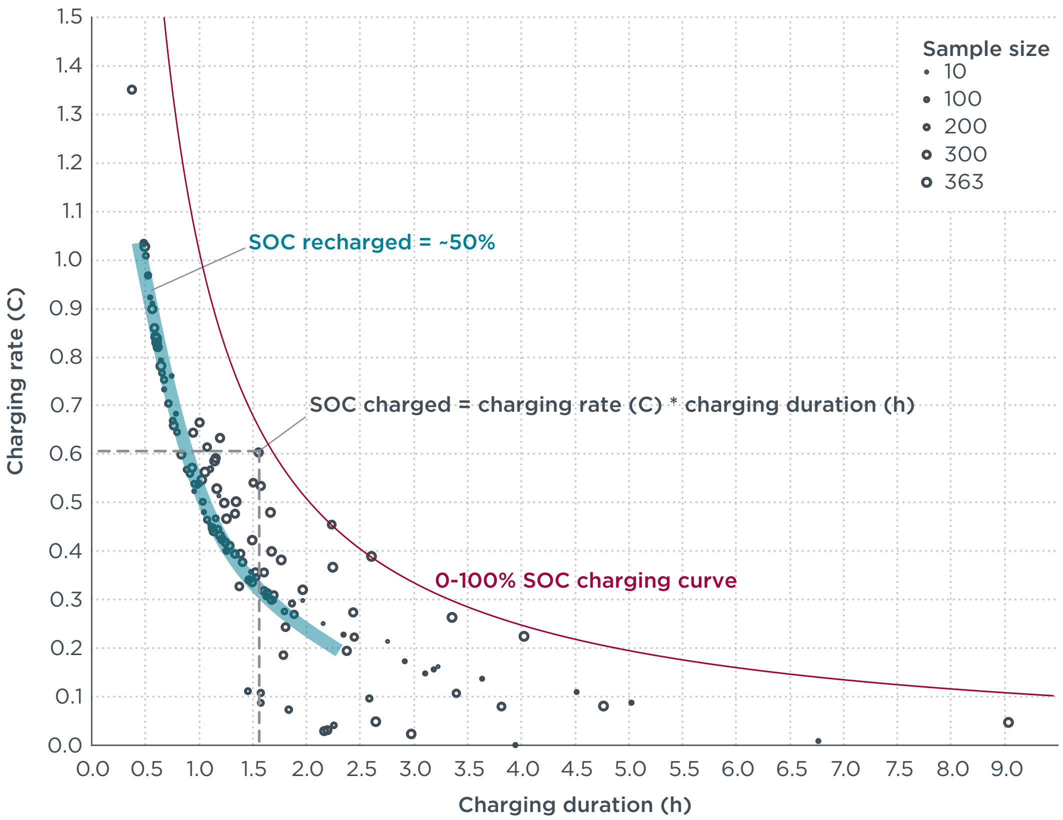

Figure 6. Charging rate and duration of the electric HDVs in the sample.

Figure 7 shows the ranges of charging SOC, and the data show that over 60% of charging activities began in the 30%–60% charging range; on the other hand, more than 70% of charging events terminated at an SOC greater than 90%. (We assumed anything over 90% SOC to be fully charged because more granular data was not available.)

This pattern also echoes what is shown in Figure 6. In general, 60%–70% of total SOC is the most that many fleet operators appear to be comfortable consuming. Fleet operators charge several times per day, likely to ensure readiness whenever the vehicle might be needed.

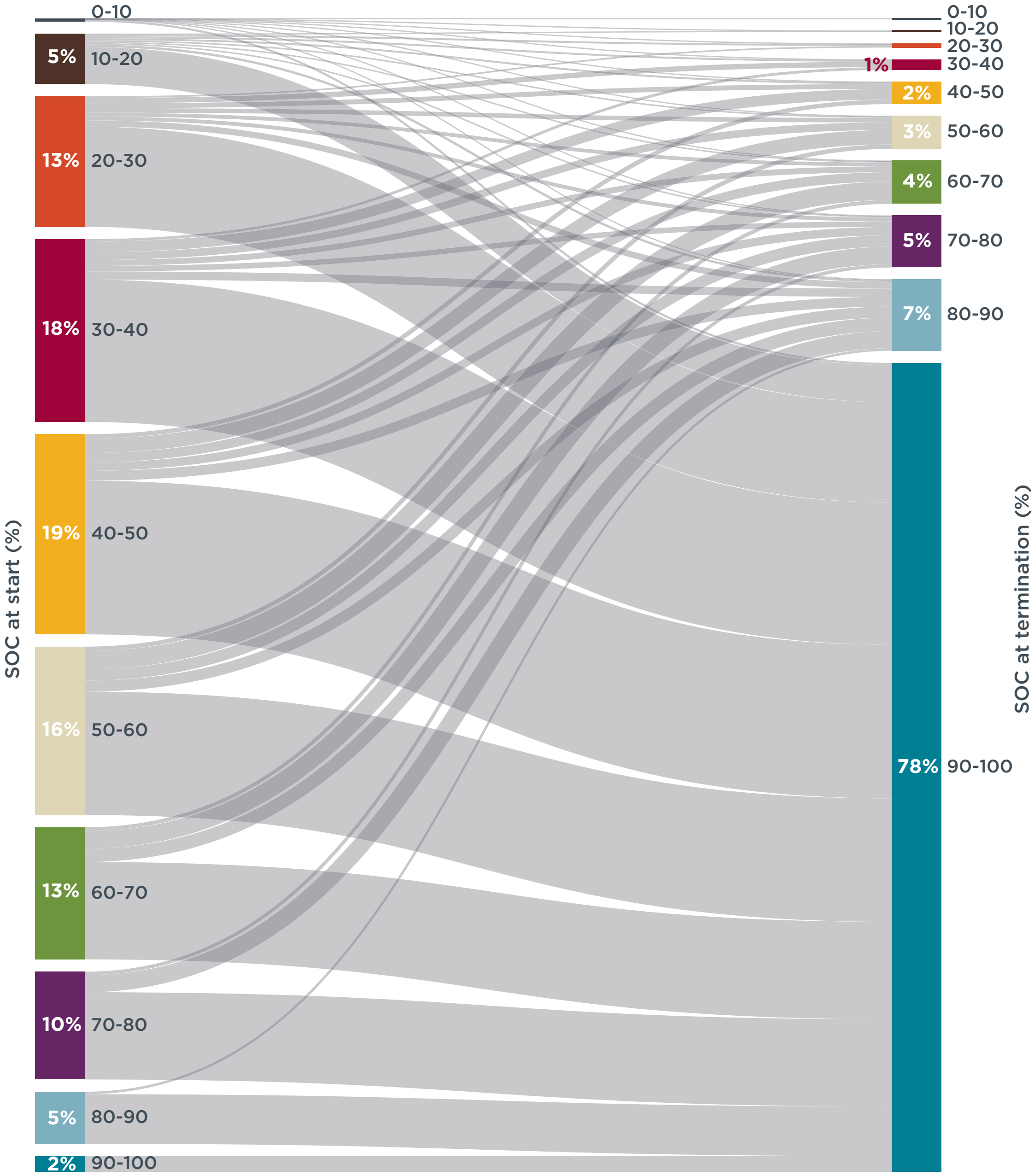

Figure 7. Sankey diagram showing the flow of the starting (left) and ending (right) SOC (%) of charging events. Each side represents the share of charging events starting or ending with a specific SOC bin, adding up to 100%. The width of lines is proportional to the number of events.

Figure 8 presents the start and termination times of charging activities for electric HDVs. Overnight hours and the hours around noon were when most charging activities happened. Specifically, the most frequent periods for charging were 22:00–23:00, 0:00–1:00, 0:00–2:00, and 12:00–13:00 (the blue bands in the figure). Additionally, overnight charging generally took longer; it usually started between 21:00 and 22:00 and ended between 01:00 and 03:00, so about 3–4 hours of total charging (the red bands in the figure). In contrast, daytime charging was generally finished within 1 hour.

This charging behavior suggests that depot charging is still important to have prior to owning a fleet of electric HDVs. The “charging whenever possible” strategy supports daily operations, but multiple charging activities during the day seem to still be a preferred pattern of work in real-world application.

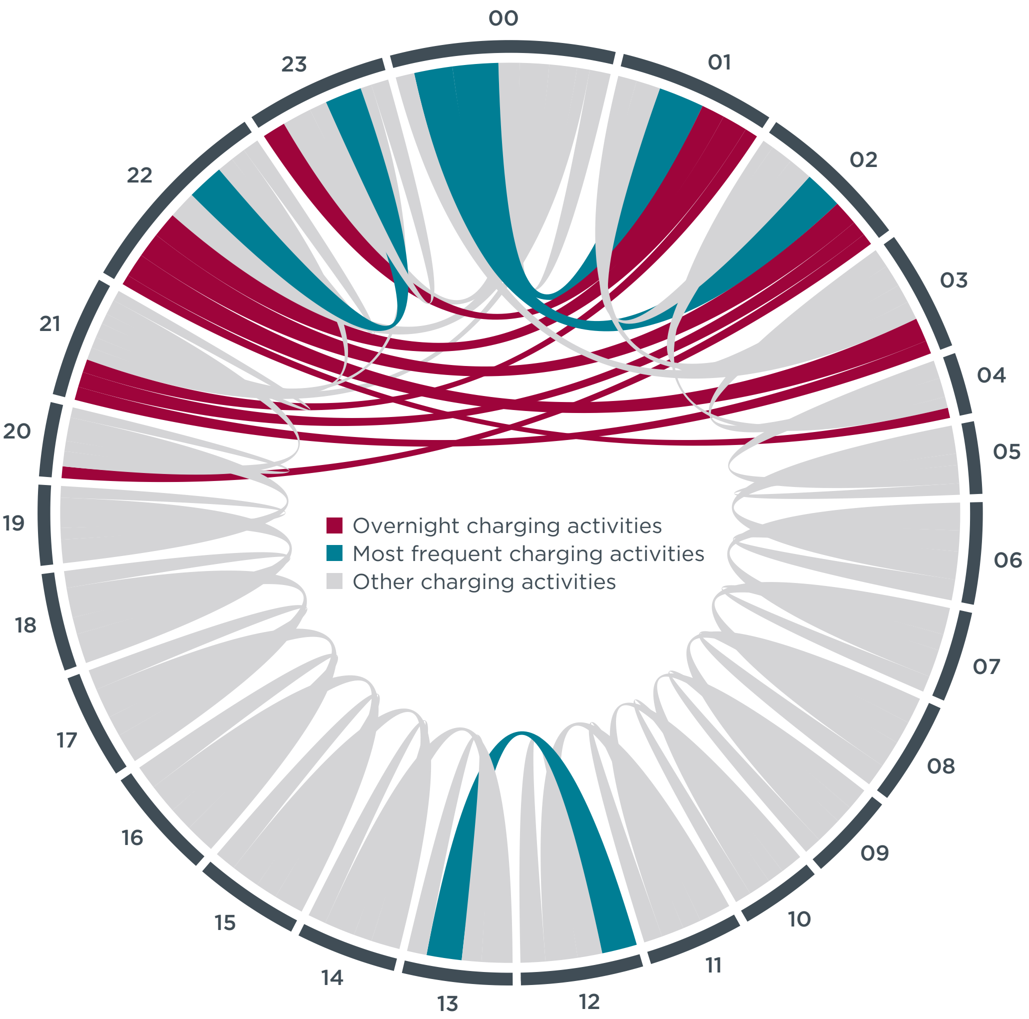

Figure 8. Time and duration of charging events. Time starts at 00:00 and goes clockwise to 23:00. The accuracy of the arc is an hour. An arc going from 12 to 13 means the charging event started anytime from 12:00:00 to 12:59:59 and ended anytime from 13:00:00 to 13:59:59. Overnight charging is defined as an event spanning across 00:00. Most frequent charging activities are defined to as those in the top four most frequent event windows. A charging event ends when the battery is fully charged or has reached the desired charge level.

KEY TAKEAWAYS AND POLICY OPPORTUNITIES

In this project, we evaluated nine battery electric HDV models in 18 cities of China with a total sample size of 11,993. Aggregated data from full calendar year 2021 was collected and the main objective of this report was to analyze the real-world energy performance and to identify the charging behavior of electric HDV fleet operators. For all categories, vehicles displayed less electric range in daily operations than the nominal values suggest, and in an extreme case, electric trucks were about 40% inferior to the nominal range. The real-world ranges were mostly consistent across cities, which implies that climate and geographical terrain conditions are not necessarily key elements in procurement decisions. Based on these results, we provide the following suggestions to policymakers in China:

Extend the type-approval procedure for determining the electric driving range to include cold and hot ambient temperatures. In most cases for "cold" (<0°) and "hot" (>30°) ambient temperature, the average energy consumption of electric HDVs was found to surpass the nominal values by over 50%. As a benchmark of energy consumption, type-approval procedures could take more working conditions into consideration to better reflect real-world performance.

Use drive cycles that are representative of the vehicle application when certifying the electric driving range. The current standard still applies outdated HDV testing cycles. In addition to adopting more localized cycles for type-approval procedures, the government can make fleet operators aware of the expected real-world range through trainings, seminars, and other means. In this study, we found that a discount rate of 0.6 applied to the current nominal value is effective in estimating the real-world range of electric HDVs in most cases.

Policymakers can support operators of electric HDVs by incentivizing cost-effective charging through time-varying tariffs. This study showed that operators often started charging between 30% and 60% of SOC. About 80% of charging activities terminated when almost fully charged (i.e., greater than 90% of SOC). The starting points of SOC imply that range anxiety still exists, and fleet operators apply a strategy of "charging whenever possible," which often means charging frequently throughout a day.

Most charging for electric HDVs was done overnight, but the time from 12:00 to 13:00 was another hotspot for charging activities due to the lunch break. Overnight charging often took up to 6 hours; for daytime charging activities, the most frequent duration was within 1 hour, and this also suggests a strategy of "charging whenever possible." As energy expense is considered a significant barrier to the adoption of electric HDVs, charging less for power during the lunch break time would be favorable for operators of electric HDV fleets.

Once more, this analysis only covered select models and cities. For some models and cities, data are lacking for certain high-speed driving conditions. Additionally, model performance in the real world is affected by other factors such as topography, traffic, and driving patterns. More research and analysis are needed to cover more vehicle models, ambient temperatures, and geography.

APPENDIX. METRICS AND METHODOLOGY

This section lists the mathematical methods applied to calculate key performance metrics. All of the energy consumption and ranges shown in the paper are based on median values of the data sample.

$$\textit{Energy consumption (kWh/100km)} = \frac{\Sigma(SOC_{start,i} - SOC_{end,i}) \times capacity_i}{\Sigma(mileage_{end,i} - mileage_{start,i})/100)}$$

where:

i	a trip, which is identified by a driving event
SOC_{start} (%)	state of charge when a trip begins
SOC_{end} (%)	state of charge when a trip ends
capacity (kWh)	MIIT nominal battery capacity
$mileage_{start}$ (km)	mileage when a trip begins
$mileage_{end}$ (km)	mileage when a trip ends

$$\textit{Range (km)} = \frac{\Sigma(mileage_{end,i} - mileage_{start,i})}{\Sigma(SOC_{start,i} - SOC_{end,i})}$$

where:

i	a trip, which is identified by a driving event
SOC_{start} (%)	state of charge when a trip begins
SOC_{end} (%)	state of charge when a trip ends
$mileage_{start}$ (km)	mileage when a trip begins
$mileage_{end}$ (km)	mileage when a trip ends

$$\textit{Charging duration (h)} = \frac{\Sigma time\_span_i}{3{,}600}$$

where:

i	a charging event
time_span (s)	duration of a charging event

$$\textit{Charging rate (C)} = \frac{\Sigma SOC_{end,i} - SOC_{start,i}}{\Sigma Charging\ Duration_i}$$

where:

i	a charging event
SOC_{start} (%)	state of charge when a charging event begins
SOC_{end} (%)	state of charge when a charging event ends
Charging duration (h)	duration of a charging event

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