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Real-world performance of battery electric passenger cars in China

ENERGY CONSUMPTION, RANGE, AND CHARGING PATTERNS

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INTRODUCTION

Electric vehicle technologies have great potential to reduce the air pollutant and greenhouse gas emissions from motor vehicles. China is one of the world's most successful electric vehicle markets, and vehicle electrification will be a critical component of realizing the nation's carbon peaking and carbon neutrality goals, which were first announced at the United Nations General Assembly in September 2020.[1]

This report offers a range of stakeholders, including consumers, businesses, governments, and researchers, analysis of the real-world performance and use pattern of battery electric passenger cars based on a large set of real-world data. National Consumers Association data from 2021 showed that one of the major complaints about new energy vehicles (NEVs) was that their range on the road was less than that indicated by the nominal values.[2] (In China, NEVs are battery electric, plug-in hybrid electric, and hydrogen fuel cell electric vehicles.) The nominal values are from the type-approval certification process, and these are reported publicly by the automakers and the Ministry of Industry and Information Technology (MIIT) of China. For consumers and businesses, the information in this report can shed light on vehicle performance. Such analysis also supports policymakers in designing future policies related to things like improving vehicle labels for the consumer; incorporating test cycles that account for real-world conditions such as higher speeds, air conditioning use, and colder ambient temperatures; and improving charging infrastructure planning.

The data for this study comes from the open lab of the National Big Data Alliance of New Energy Vehicles (NDANEV), an organization that aims to better monitor and manage the operation of NEVs. The open lab of NDANEV has been in operation since the beginning of 2017, and NEVs are required to be connected to it. The total number of vehicles connected exceeds 9.2 million, which is about 90% of China's NEV stock, and total mileage of over 300 billion kilometers was recorded by July 17, 2022.[3] Vehicles upload operational data every 30 seconds, and raw data include status, speed, accumulated mileage, current, voltage, battery temperature, and state of charge, and more.

Figure 1 shows the flow of work for this analysis. ICCT set the scope, metrics to investigate, and methodology based on the parameters that are contained in the event-level data. Data privacy restrictions prevented us from obtaining the raw data, and instead, the open lab of NDANEV processed the raw data based on the methodology we specified and shared the aggregated data. ICCT has not independently verified the data because we have no access to the raw data.

1 Fiona Harvey, "China Pledges to Become Carbon Neutral Before 2060," *The Guardian*, September 22, 2020, https://www.theguardian.com/environment/2020/sep/22/china-pledges-to-reach-carbon-neutrality-before-2060

2 China Consumers Association, "Analysis and Release of Complaints Received by the National Consumers Association in 2021," news release, January 28, 2022, https://cca.org.cn/tsdh/detail/30346.html.

3 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

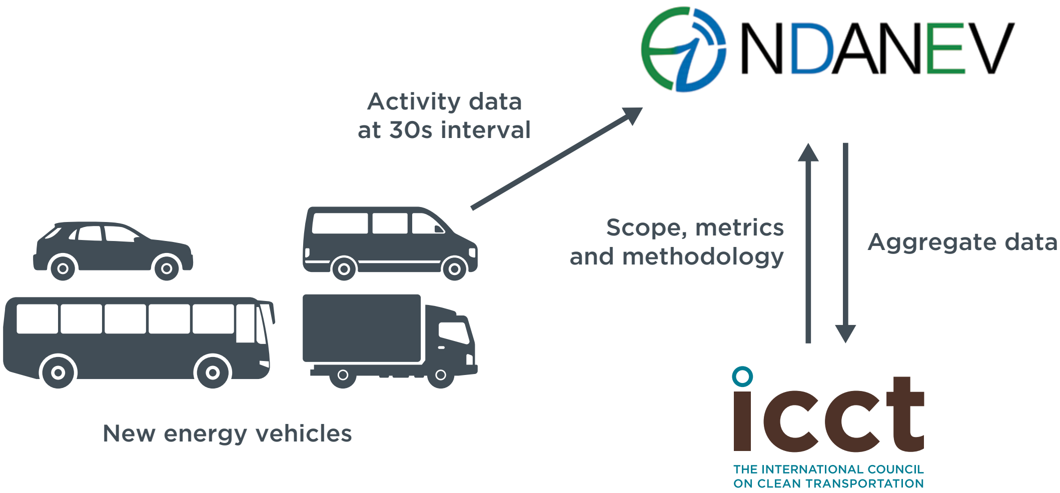

Figure 1. Data and workflow between ICCT and the open lab of NDANEV for this analysis.

SCOPE AND METHODS

We identified the 10 best-selling passenger car models in China during the period from 2017 to the end of 2021. The vehicle operations data analyzed is from full calendar year 2021. The data set analyzed included only private-use vehicles of those 10 models that were registered in five selected cities in 2021. The five cities are Shenyang, Beijing, Hangzhou, Chengdu, and Guangzhou, and that yielded a total data set of over 140,000 vehicles. More details of the sample size for each model in each city are in Appendix A, which also outlines the methods used to calculate the key real-world performance metrics from the different parameters in the event-level data.

Table 1 lists the key features of the selected models based on the public information in MIIT's Catalogue of Recommended Models for the Promotion and Adoption of New Energy Vehicles. These are the nominal values for energy consumption and range based on type-approval certification.

Table 1. MIIT information about key features of the selected models, listed in ascending order of the difference between nominal and real-world range under the "very cold" (≤ -7 °C) driving conditions (car with the smallest difference is listed first). Length, width, and weight are rounded to the nearest ten.

Model	U.S. class	Length (mm)	Width (mm)	Gross vehicle weight (kg)	Energy consumption (kWh/100 km)	Range (km)
Car 1	**City car***	2,920	1,490	1,020	9.3	170
Car 2	**SUV**	4,750	1,920	2,340	13	525
Car 3	**Compact**	4,690	1,850	2,020	12.4	445
Car 4	**Mid-size**	4,980	1,910	2,400	14.1	605
Car 5	**Compact**	4,690	1,850	2,170	12.6	468
Car 6	**Compact**	4,650	1,820	1,980	13.9	416
Car 7	**City car**	3,500	1,660	1,300	10.2	351
Car 8	**Compact**	4,680	1,770	2,030	13.5	405
Car 9	**Small SUV**	4,100	1,790	1,870	13.6	305
Car 10	**City car**	2,920	1,490	980	8.8	120

* Also known as minicompact. In China, these are generally called microcars, a term that is used for the smallest size of cars that have a wheelbase between 2 m and 2.3 m and a length generally under 3.65 m. Their appearance resembles that of a Smart Fortwo or Fiat 500.

The five cities were chosen because they are dispersed throughout the country and have different climates (Figure 2). Shenyang has the lowest average temperature in winter and Guangzhou rarely has temperatures below 0 °C.

Figure 2. Location of the five selected cities.

To emphasize, this analysis only covers select models and cities, and it is based on 2021 data and not on any more recent performance. For some models and cities, data are lacking for certain real-world conditions, including "hot," "cold," "very cold," and "high speed." Moreover, performance in the real world is affected by other factors such as topography, traffic, and driving patterns. Also note that the values shown in Figures 3–6 below, for both energy consumption and range, are all based on the median values of the sample.

ENERGY CONSUMPTION

In this report, energy consumption is presented in kWh per 100 km and Figure 3 depicts energy consumption by model and city. The ambient temperature is daily average temperature rather than for each trip. In Figure 3 we selected the medium speed bin of 30–60 km/hr to exclude impact of speed and isolate the impact of ambient temperature; ≤ -7 °C is "very cold;" ≤ 0 °C is "cold" (all temperatures that are ≤ 0 °C, including ≤ -7 °C); and 30 °C–35 °C (> 30 °C and ≤ 35 °C) is "hot" (none of the data in our sample was from a day with an average ambient temperature above 35 °C). We also selected a medium temperature bin of 10 °C–25 °C to exclude ambient temperature impact and isolate the impact of driving speed; > 90 km/hr is considered "high-speed" driving.

Some of the cities do not have all of the data points reflected in Figure 3. This is due to limited data for high-speed driving and limited days with high or low temperatures in 2021. For example, only Shenyang and Beijing had any days with ≤ -7 °C temperature, and these two plus Hangzhou were the only cities with more than two days (and at least one day below 0 °C) of data points for ≤ 0 °C.

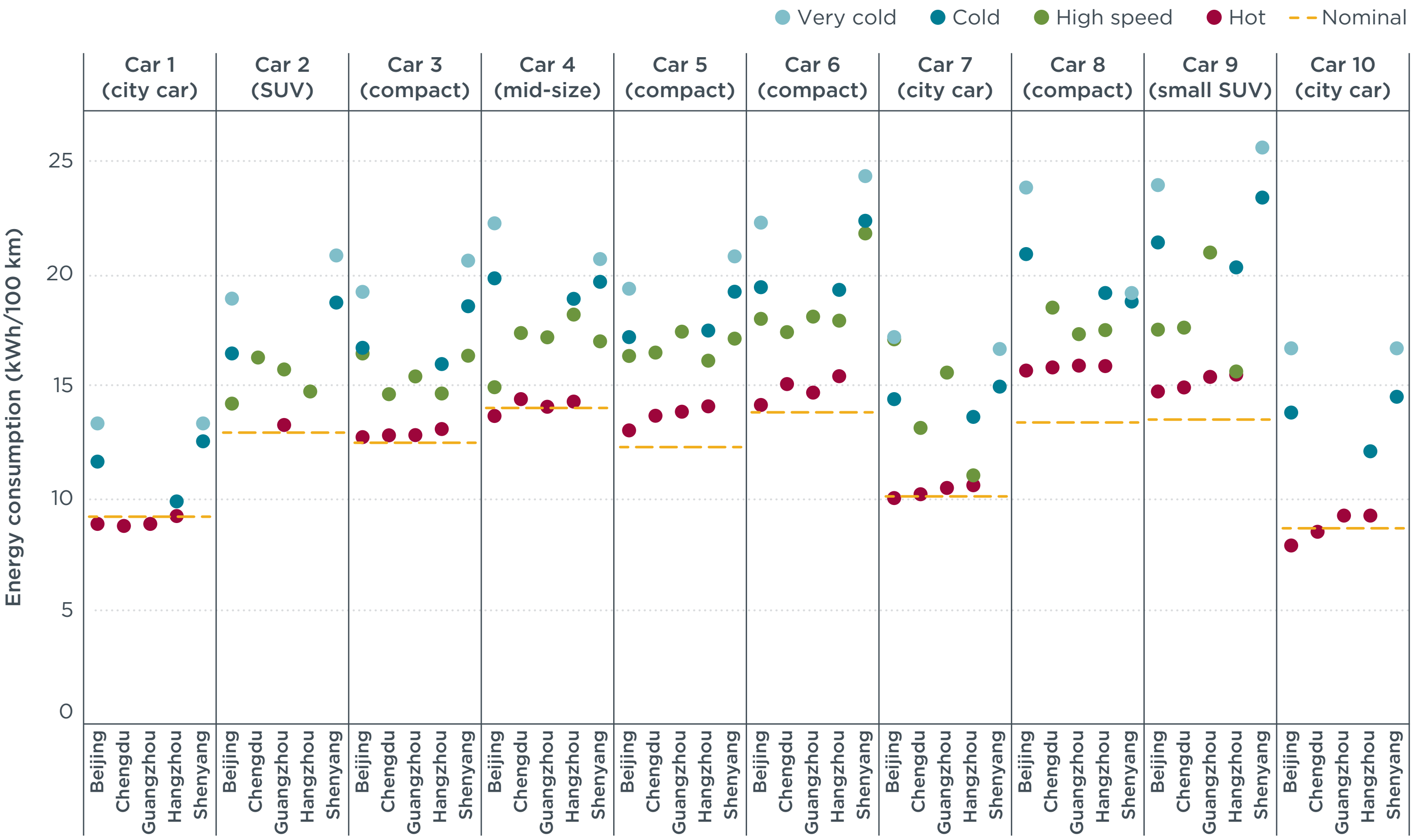

Figure 3. Real-world energy consumption under different ambient temperatures and under high-speed driving by model and city. Models are listed in the same order as in Table 1.

For almost all cities and models, low ambient temperature had the most adverse impact on energy consumption. In Shenyang, the city with the coldest average temperature in winter, the increase in energy consumption in "cold" conditions was found to range from 35% to 75% compared to nominal values. For Beijing and Hangzhou, which tend to have slightly higher winter temperatures, the increase in energy consumption across models was found to be between 25% and 60%, and 7% and 50%, respectively, in "cold" conditions. The increase in energy consumption in "very cold" conditions was similar in Shenyang and in Beijing, and it ranged from 40% to 90%.

High-speed driving also increased energy consumption, and the highest increases were over 55% for car 7 in Beijing and for car 6 in Shenyang. The impact of "hot" weather varied, and depending on the model and the city, energy consumption either increased or decreased. Still, this impact was less significant than that of low ambient temperature and high-speed driving.

In Figure 4, we compare energy consumption under different real-world driving conditions by model, aggregated across all cities. Data points for all conditions, represented by the dark gray color, incorporate all operation data regardless of city, temperature, or speed. The increase in energy consumption compared to nominal values in "very cold" and "cold" conditions ranges from 40% to 90%, and 30% to 65% respectively. This is followed by "high-speed" conditions, which increase energy consumption by 20% to 35%. In "hot" conditions the impact is less significant, and the increase is within 20%. Under "all conditions," energy consumption is generally higher than nominal values, but there are clear differences by model. Cars 1, 2, 7, and 10 had smaller differences between their nominal values and real-world driving, and cars 5 and 8 showed larger differences.

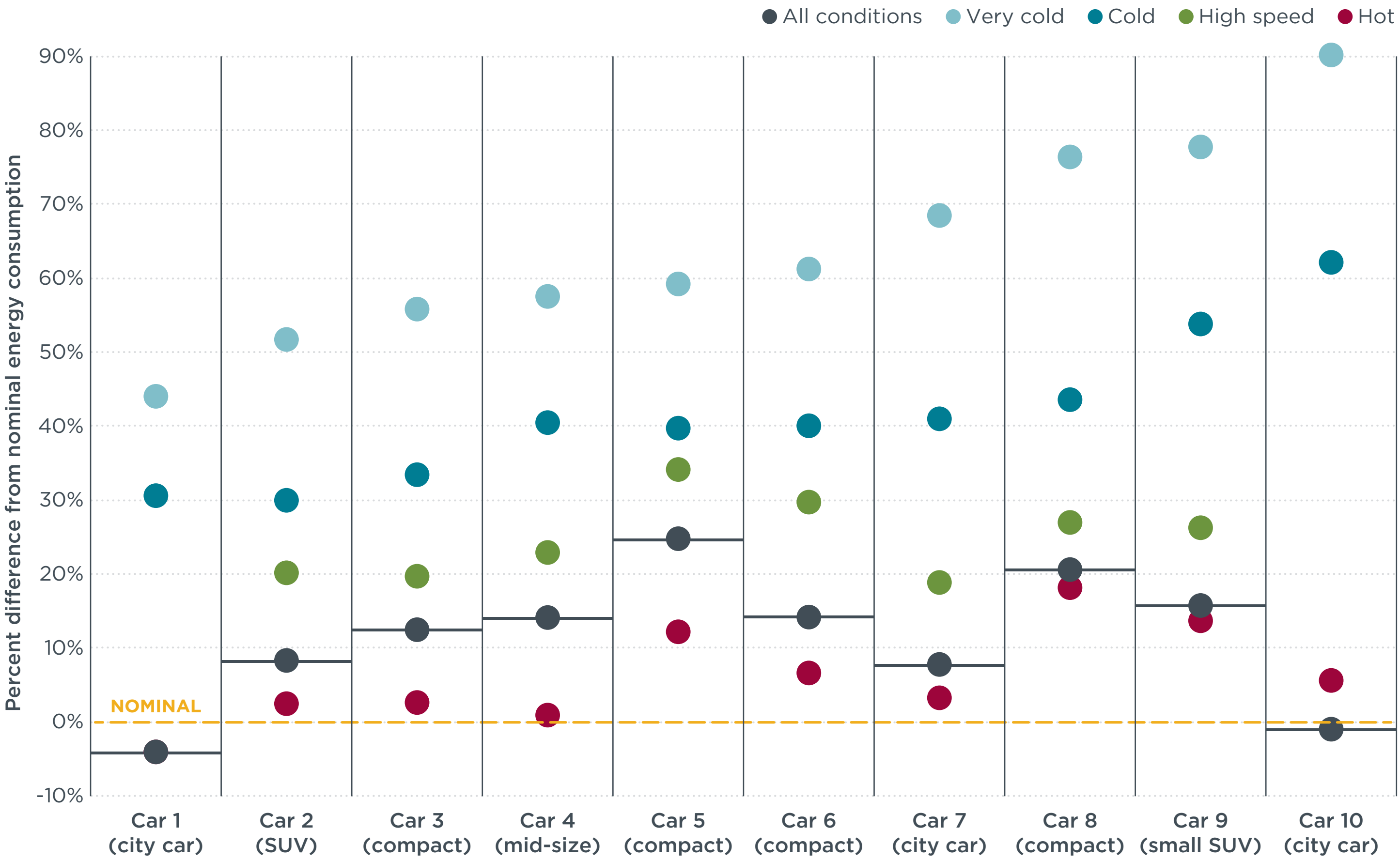

Figure 4. Real-world energy consumption's percent difference from nominal values (nominal shown as the yellow line) under different conditions by model. "All conditions" is the value under all driving conditions and models are listed left to right in the same order as in Table 1.

ELECTRIC RANGE

Because the open lab of NDANEV does not have direct information about range, we calculated this value based on each trip. Calculating range based on trips, especially when without access to raw data, introduces uncertainty in ways that it does not when calculating energy consumption. For one thing, downhill trips could result in a very large range that requires careful data filtering. In addition, due to computational cost limitations, the aggregate values of range were only available to us under all driving conditions and these were not separated by temperature and speed bins. Thus, in this paper, real-world values for electric range were obtained by calculating based on the difference of energy consumption in the real world compared to nominal energy consumption, and the nominal range. In Figure 5 we illustrate the real-world electric range values that correspond to the energy consumption shown above. Across all models and cities, “very cold” and “cold” conditions were found to reduce electric range by 30% to 50%, and 20% to 40%, respectively, compared to nominal values. We see a less significant effect under “high-speed” conditions, but still there was reduced electric range of between 15% to 25%. The impact of “hot” conditions varied; it increased range by 5% for one model but generally reduced it up to 15%. Under “all conditions,” electric range was on average 15% lower than nominal values across these 10 models.

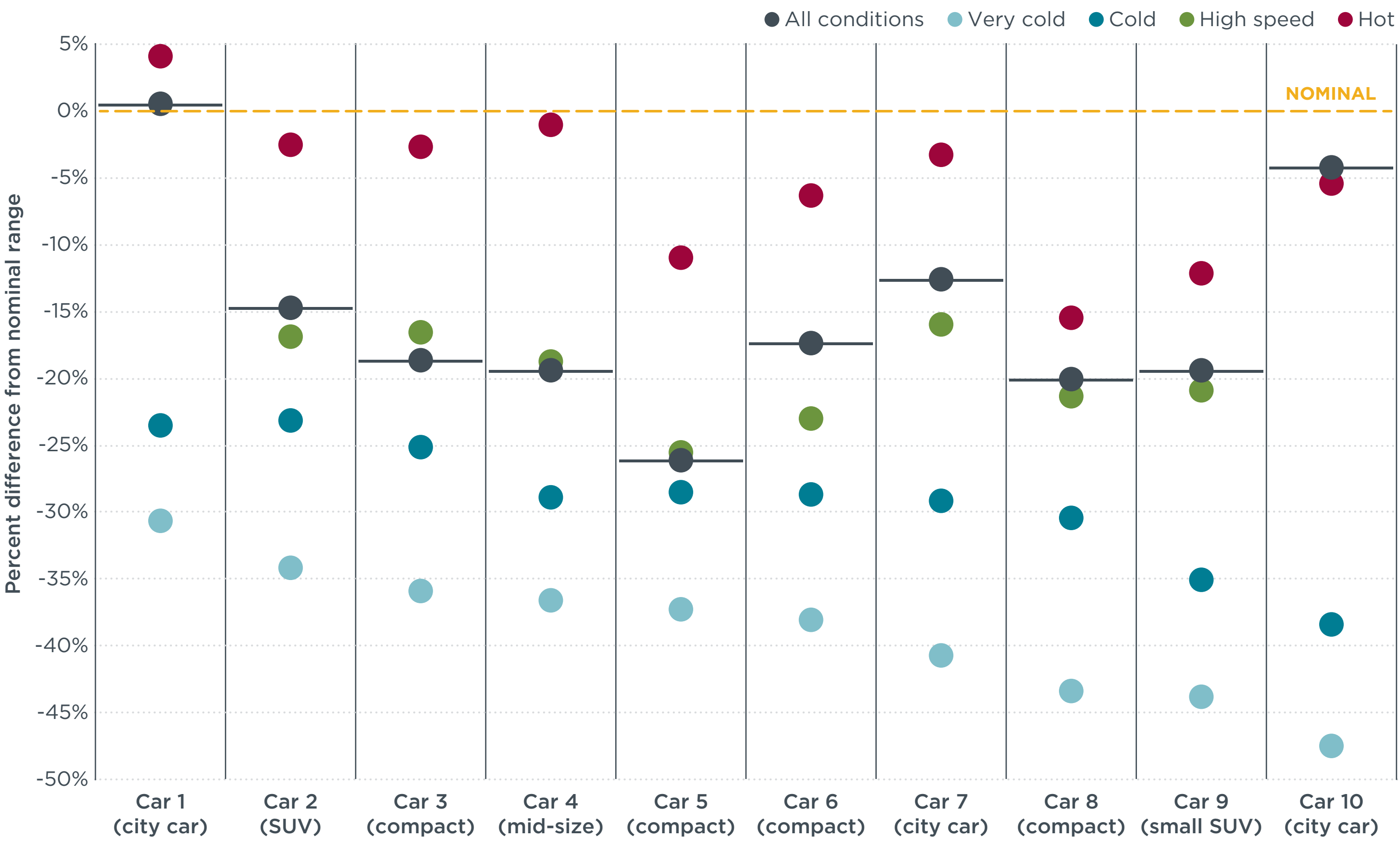

Figure 5. Real-world electric range’s percent difference from nominal values (nominal shown as the yellow line) under different conditions by model. “All conditions” shows the value under all driving conditions and models are listed left to right in the same order as Table 1.

The data show that for the same model, the real-world electric range varied substantially by city due to factors including but not limited to climate, topography, and driving style (Figure 6). For example, the range of car 4 was lowest in Shenyang and highest in Guangzhou, at 20% and 5% lower than its nominal value, respectively. Models with a shorter range and smaller size showed less variance, and this was the case for cars 1, 7, and 10, all of which are city cars. One potential reason for this is that they are typically used in a relatively fixed setting—the daily commute to and from work.

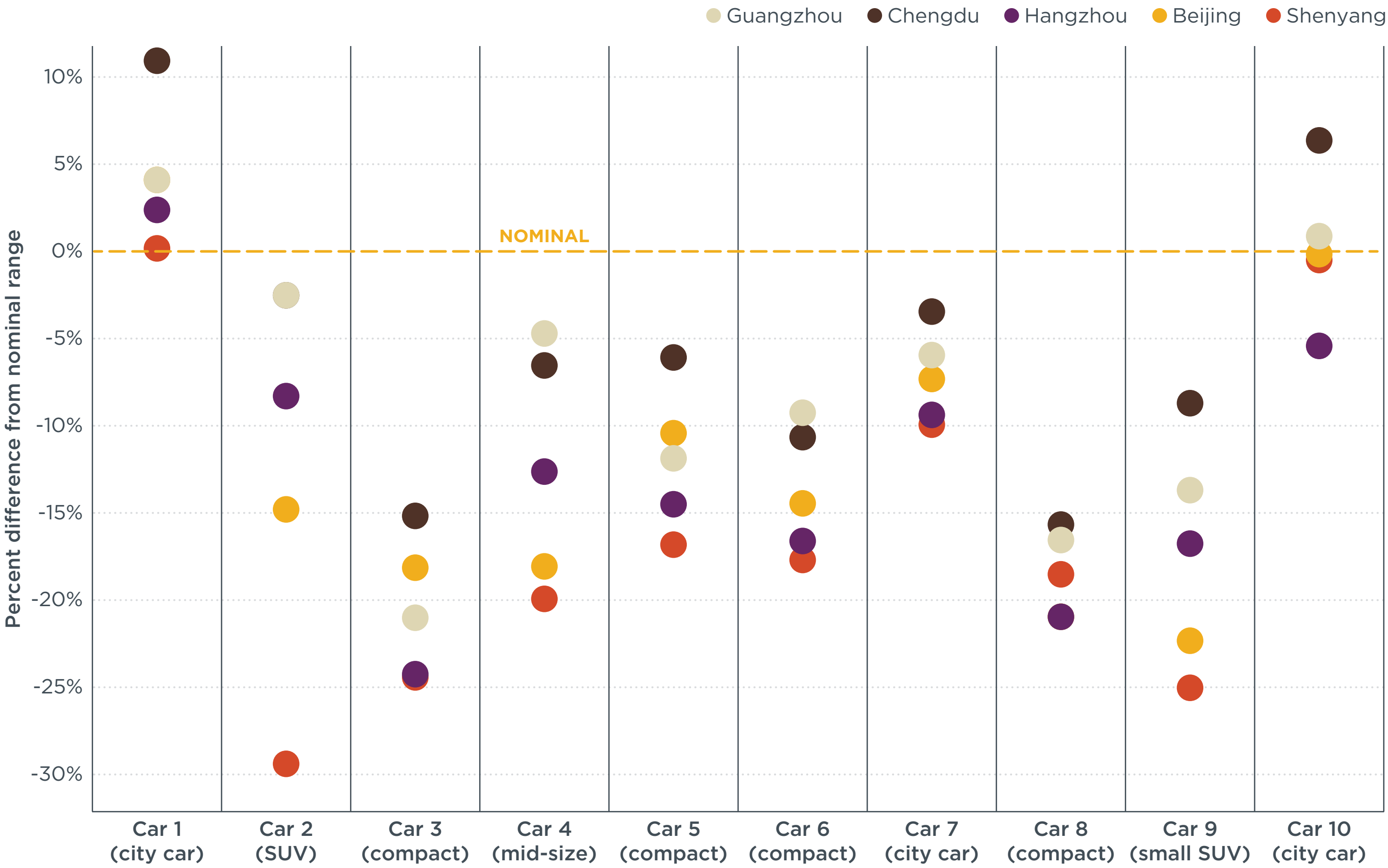

Figure 6. Percent difference in real-world electric ranges under "all conditions" compared to nominal values (nominal shown as the yellow line), by model and city. Models are listed left to right in the same order as Table 1.

CHARGING PATTERNS

Charging rate, or C-rate is commonly used to measure the speed at which a battery is fully charged or discharged. In this analysis, a "fast charger," which is capable of a "fast charging event," is defined as a charging rate above 0.5C. 0.5C means that the battery is charged from 0% to 100% in 2 hours.

As shown in Figure 7, Guangzhou, Hangzhou, and Chengdu saw the highest utilization of fast chargers in terms of total number of charging events. One of the factors that contributes to this is that more than half of the installed public chargers in these cities are fast chargers. In all cities in our sample except Guangzhou, the share of charging events that used a fast charger is lower than the fast chargers' share of total public chargers because many non-public chargers are slow chargers. In the case of Guangzhou, the greater reliance on public chargers might indicate that EV drivers prefer fast chargers or that they have less access to private chargers. Almost all of Shenyang's public chargers are fast chargers, but the total number is low compared to other cities and most of the charging was with slow chargers, most likely home chargers.

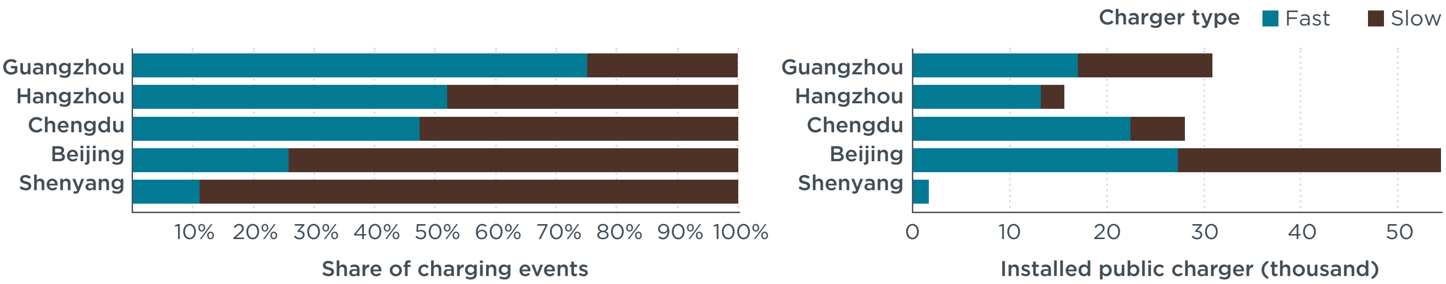

Figure 7. Share of charging events, including public and home chargers, by charger type (left), and number of installed public chargers (right).

Figure 8 shows that cars 1 and 10, which are city cars, were exclusively charged using slow chargers. Recall that these vehicles have a shorter range and are typically used mainly for daily commute. As the daily use is limited, they are more conveniently charged at home with a slow charger. At the same time, cars 2 and 4, which have the longest range of the selected models, were also mainly charged with slow chargers. This is likely because drivers do not experience much range anxiety and thus charge at the end of the day at home or use public or workplace slow chargers when available.

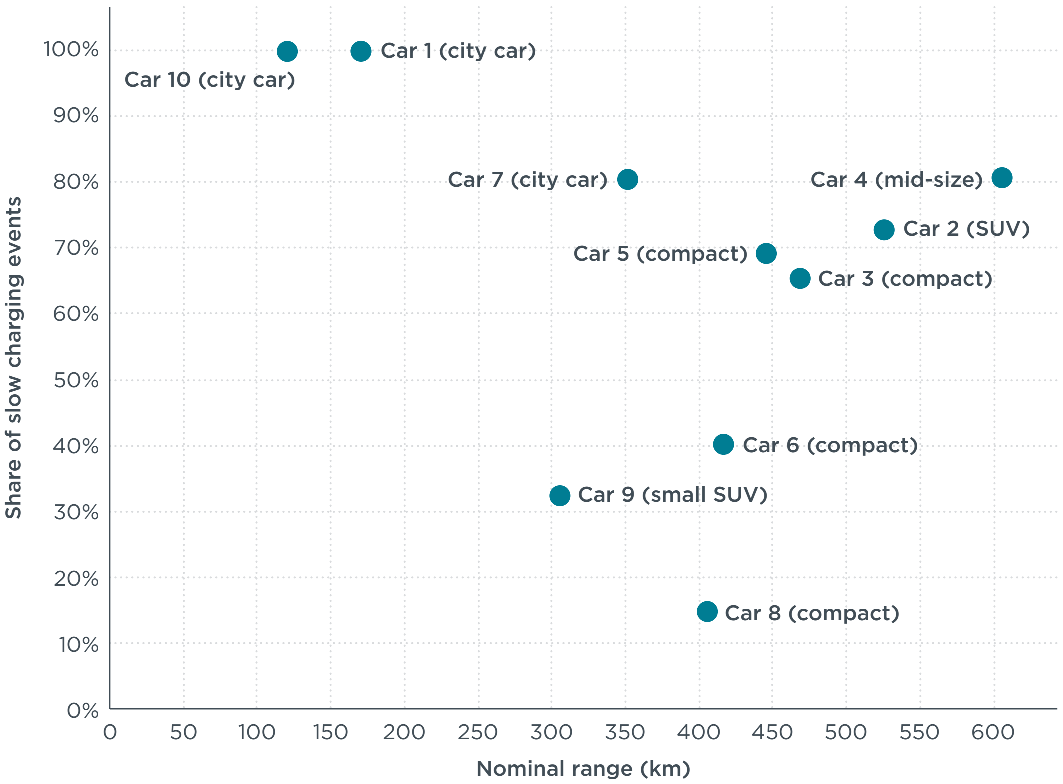

Figure 8. Share of slow-charging events by model and nominal range.

When we analyzed the state of charge (SOC) of the battery at the start of charging events in the data set, we found it was distributed largely evenly between 10% and 70%, and for over 70% of the events, the ending SOC was between 90% and 100% (Figure 9). Around 10% of charging events happened at an SOC of over 70%. This suggests that vehicle drivers might have had range anxiety and were charging whenever a charger was available, regardless of SOC, and kept charging until the battery was fully or almost fully charged.

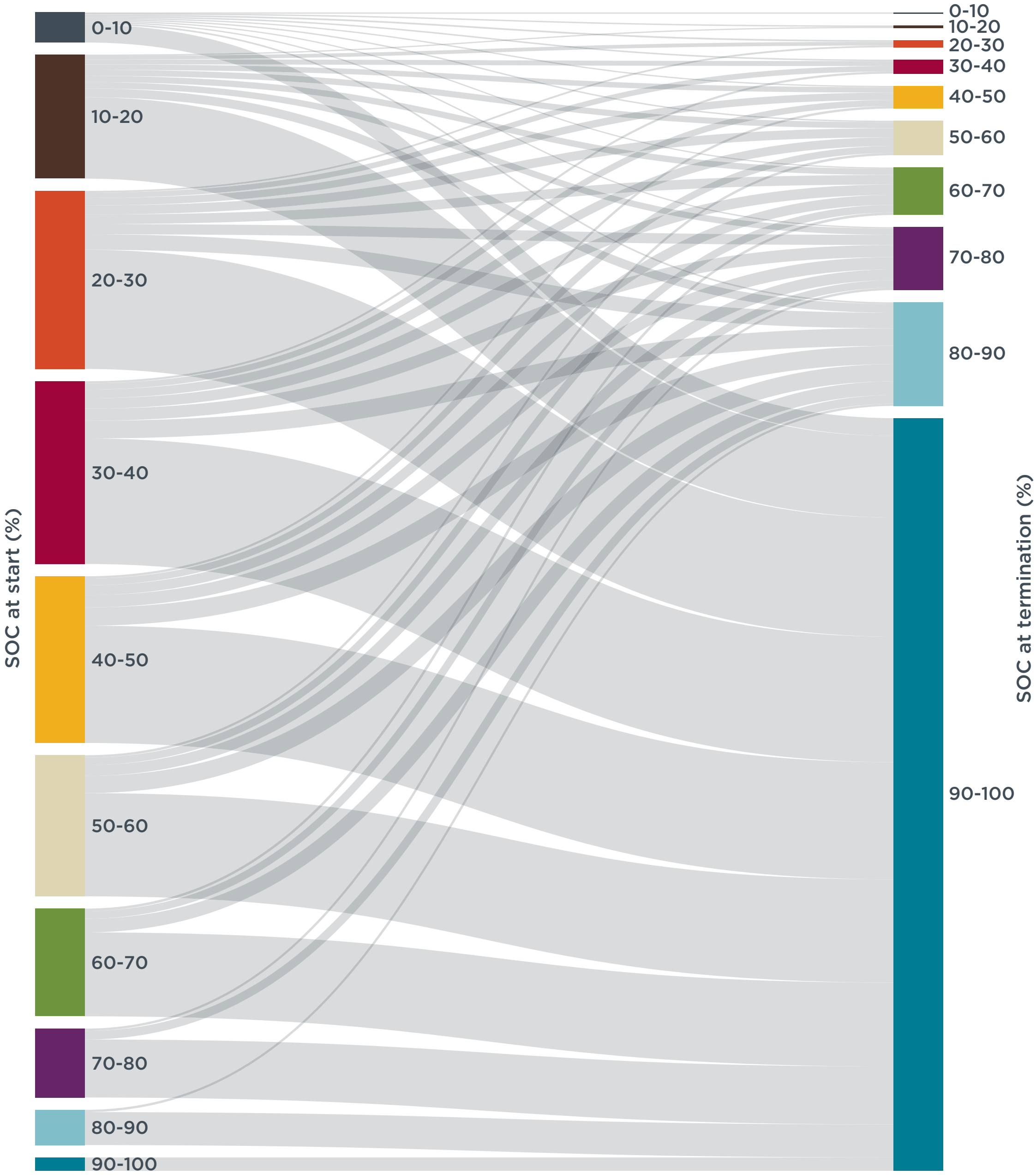

Figure 9. Sankey diagram showing the flow of the starting (left) and ending (right) SOC (%) of charging events. Each side represents the share of charging events starting or ending with a specific SOC bin, adding up to 100%. The width of lines is proportional to the number of events. Figure made using a random sample of 1% of charging events in the data sample.

In Figure 10, we see when charging events took place and their duration (i.e., the time it took to fully charge or until the SOC set by the driver was reached), and for this we included both private cars and taxis as a comparison. For both vehicle types, many drivers chose to charge during lunch hours. For private cars, another period when charging was frequent was between 3 pm and 7 pm, when many people are done with their workday. For taxis, there was frequent charging during an afternoon peak from 2 pm to 5 pm. As the change between the two shifts/drivers usually happens around 6 pm, this is likely due to the need to charge after a day's driving and before another driver's shift.

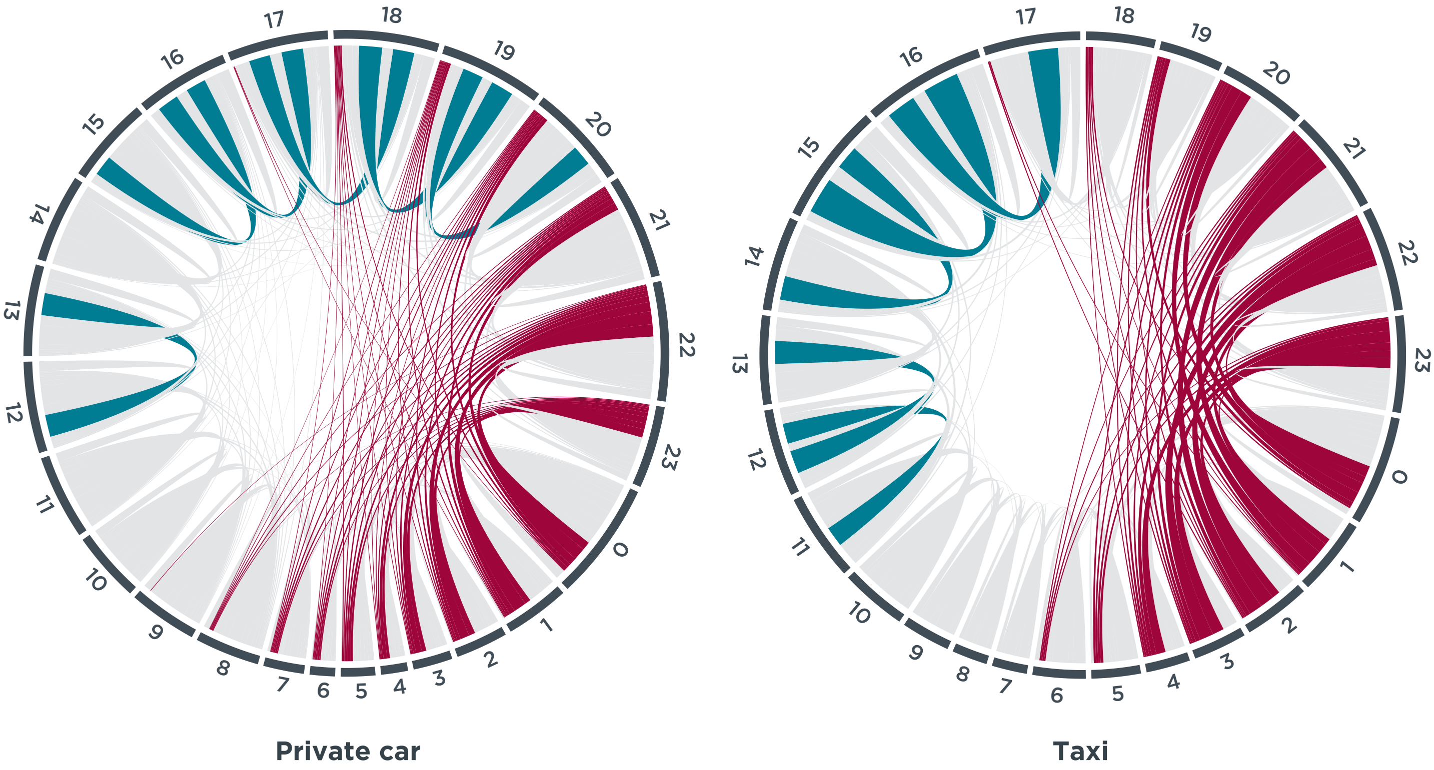

Figure 10. Time and duration of charging events for private cars and taxis. Time starts at 00:00 and goes clockwise to 23:00. Accuracy of the arc is hour. An arc going from 12 to 13 means the charging event started anytime from 12:00:00 to 12:59:59 and ended anytime from 13:00:00 to 13:59:59. Overnight charging is defined as an event spanning across 00:00. Highest frequency is defined as above 99th quantile of count of event. A charging event ends when the battery is fully charged or has reached the desired charge limit. Figure made using a random sample of 2‰ of charging events in the data sample.

The charging pattern of private cars is more disperse than it is for taxis. This could be because private use drivers are charging when there is an opportunity, and that is likely to be at least partially reflective of range anxiety. This can be understood as a kind of opportunity charging on the part of private use drivers and it is usually less than 2 hours before the car is fully charged or has reached the SOC limit that the driver set. There are also more thinner grey lines on the right and left half of the circle for private cars, which reflects a variety of overnight charging and some likely workplace charging from morning to afternoon.

KEY TAKEAWAYS AND POLICY OPPORTUNITIES

Using real-world operations data from 2021 for more than 140,000 vehicles, this paper analyzed the performance of 10 popular battery electric passenger car models in five cities in China. We found that the vehicles' range, on average, was about 15% lower than nominal values. The reduction in range was greater during low-temperature and high-speed driving.

Of the parameters examined, low ambient temperature had the most adverse impact on both energy consumption and range. On average, "very cold" (≤ -7 °C) and "cold" conditions (≤ 0 °C) reduced electric range by 30% to 50%, and 20% to 35% respectively, compared to nominal values, and the range for some models in Shenyang was reduced by half in "very cold" conditions. "High-speed" driving (> 90 km/hr) also negatively impacted energy consumption and range, but generally not as much as low temperature. On average, range was reduced by 15% to 25% in "high-speed" driving, and some models had as high as a 40% reduction. The impact of "hot" temperature (30 °C–35 °C) varied and was less significant than low temperature or high-speed driving. "Hot" temperatures generally reduced electric range by up to 15%, likely due to the use of air conditioning.

Charging patterns seem to suggest range anxiety and that drivers charged when there was an opportunity, regardless of remaining SOC. Additionally, the prevalence of public charger type (fast versus slow) and vehicle range both appear to contribute to drivers' decisions about which type of charger to use (Figures 7 and 8). The period around noon and the period from afternoon to evenings saw the most charging.

Large differences between nominal and real-world performance in certain conditions could hinder wider adoption of NEVs if more is not done to provide real-world information to consumers and to educate vehicle drivers about how to support optimal performance. Nominal values that differ significantly from real-world performance can result from unrealistic regulatory test procedures, sub-optimal efficiency technologies from vehicle development or manufacturing, sub-optimal use behaviors from consumers, or some combination of these. It is clear that consumers in China have concerns, and in response, consumers associations in Beijing, Tianjin, and Hebei Province previously tested 10 models under cold environment (-10±2 °C).[4] Their tests were based on guidance in the 2017 type-approval test procedure, and the results showed that the range under the test was on average 64% of the range reported by automakers. The updated 2021 test procedure for energy consumption and range of electric light-duty vehicles in China, which is the current procedure, includes methods for testing under hot and cold temperatures, but only for information purposes in the appendix and such testing is not mandatory.[5] To help narrow the gap between nominal and real-world performance and ease consumer concerns, we offer the following suggestions to the government, industry, and consumers.

Government: The energy efficiency of battery electric cars could be enhanced by introducing increasingly tightened efficiency standards that include realistic and robust test procedures and official vehicle efficiency labels for consumer awareness. Specifically:

» The efficiency standard could be amended to include processes and measures that better reflect real-world performance.

4 Charge full at 20 °C–30 °C and air-conditioning on. Test procedure is based on GB/T18386-2017. China National Radio, "Beijing, Tianjin, Hebei Consumers Associations Released the Results of the Electric Vehicle Range Under Cold Temperature," March 11, 2022. http://www.cnr.cn/tj/tjyw/20220311/t20220311_525762656.shtml

5 Auto-testing, "GB/T 18386.1-2021 Test Methods for Energy Consumption and Range of Electric Vehicles – Part 1: Light-duty Vehicles," March 26, 2021. https://www.auto-testing.net/news/show-110262.html

» The regulatory test procedures that determine the nominal vehicle efficiency and range values could include real-world driving conditions in China, including low (≤ -7 °C) and high test temperatures (>30 °C) and the use of the air conditioning system.

» The regulatory test procedure could include a share of high-speed driving that makes it as realistic and representative of real-world conditions as possible.

» Introduce or incorporate efficiency and range values under the real-world driving conditions described above in vehicle efficiency labels for NEVs.

» To account for the electricity demands from electric vehicles in current and future infrastructure planning, the introduction of time-of-use rates could encourage drivers to shift their charging to the times of day when the overall electricity demand is lower.

Manufacturers: Both vehicle and parts manufacturers could prioritize adopting and improving vehicle efficiency and thermal control technologies of their NEVs and could also proactively provide consumers with real-world performance data. The latter would include providing their best estimated realistic efficiency and range information as a complement to the nominal values already provided at the sales stage; providing more accurate estimates of remaining electric mileage during use; and providing clear instructions and recommendations to consumers regarding optimal battery storage and operation, including regarding temperature and SOC.[6]

Consumers: Properly use and maintain vehicles based on information from certified labels, manufacturer instructions, and other information platforms, as this can extend battery life and help maintain performance. For example, it is generally recommended not to overcharge or over discharge beyond the 20%–80% SOC zone, and to minimize exposure to high temperature.

Once more, this analysis only covered select models and cities. For some models and cities, data are lacking for "hot," "cold," "very cold" and/or "high-speed" driving conditions. Additionally, 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 types of vehicles, models, ambient temperatures, and geography. In addition, the data analyzed is from 2021, and further work is needed to assess more recent performance.

6 Maxwell Woody et al., "Strategies to Limit Degradation and Maximize Li-ion Battery Service Lifetime – Critical Review and guidance for stakeholders," *Journal of Energy Storage*, 28 (2020): 101231. https://doi.org/10.1016/j.est.2020.101231

APPENDIX A. DATA SAMPLE

Table A1 lists the sample size (number of vehicles) for each selected model and city.

Table A1. Data sample by model and city

Model	Total sample size	Beijing	Hangzhou	Guangzhou	Shenyang	Chengdu
Car 1	3,041	85	1,220	589	240	907
Car 2	24,981	5,771	7,393	6,472	618	4,727
Car 3	21,400	7,312	6,290	4,105	503	3,190
Car 4	14,595	8,031	2,089	2,294	68	2,113
Car 5	25,901	6,112	9,727	5,479	366	4,217
Car 6	20,388	8,053	3,490	7,752	78	1,015
Car 7	4,239	1,322	1,397	921	13	586
Car 8	8,430	87	1,508	6,585	2	248
Car 9	16,789	7,204	5,470	1,616	193	2,306
Car 10	1,947	70	731	392	206	548
Total	**141,711**	**44,047**	**39,315**	**36,205**	**2,287**	**19,857**

APPENDIX B. METRICS AND METHODOLOGY

This section shows the methods used to calculate the key real-world performance metrics we analyze in this paper from the different parameters in the event-level data. Figures for energy consumption and range shown in the paper are based on median values of the sample.

Energy consumption per 100 km

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

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

Note: The open lab of NDANEV does not have real-time battery capacity information. Given that all of the vehicles in our sample were within their first few years of use, we used the nominal battery capacity based on information from the MIIT.

Energy consumption per 100 km under different temperatures

When evaluating the impact of temperature on energy consumption, we chose a fixed speed range to exclude its impact. We selected the medium speed bin of 30–60 km/hr. Temperature is daily average ambient temperature and divided into -7 °C and below, (-7,0], (0,5], (5,10], (10,15], (15,20], (20,25], (25,30], and (30,35]. No data in our sample had a daily average ambient temperature of above 35 °C.

Energy consumption per 100 km under different speeds

When evaluating the impact of speed on energy consumption, we chose a fixed temperature range to exclude its impact. We selected the medium temperature bin of 10 °C to 25 °C. Speed is the average speed of a trip, and divided into [0,30] km/hr, (30,60] km/hr, (60,90] km/hr, (90,120] km/hr, and above 120 km/hr.

Real-world electric range

The range for each model shown in the paper is based on the difference of energy consumption in real world compared to nominal, and the nominal range.

$$\text{Real-world electric range (km)} = \frac{\textit{Nominal range}}{\left(1+\left(\frac{\textit{real-world energy consumption}}{\textit{nominal energy consumption}}\right)-1\right)}$$

Charging duration

$$\text{Charging duration (hr)} = \text{time\_length}/3{,}600$$

time_length (s)	duration of each charging event

Charging rate

$$\text{Charging rate (C-rate)} = 1 \,/ \left(\frac{\text{time\_length}/3{,}600}{(SOC_{end\_c} - SOC_{start\_c})}\right)$$

time_length (s)	duration of each charging event
SOC_{start_c} (%)	SOC at the start of a charging event
SOC_{end_c} (%)	SOC at the end of a charging event

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