

Article

Optimal DC Fast-Charging Strategies for Battery Electric Vehicles During Long-Distance Trips

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Abstract

The rapid adoption of electric vehicles (BEVs) has increased the need to understand how fast-charging strategies influence long-distance travel times under real-world conditions. While most manufacturers specify maximum charging power and standardized driving ranges, these figures often fail to reflect actual highway operation, particularly in adverse weather. This study addresses this gap by analyzing the fast-charging behaviour, net battery capacity and highway energy consumption of 62 EVs from different market segments. Charging power curves were obtained experimentally at high-power DC stations, with data recorded through both the charging infrastructure and the vehicles' battery management systems. Tests were conducted, under optimal conditions, between 10% and 90% state of charge (SoC), with additional sessions performed under both cold and preconditioned battery conditions to show thermal effects on the batteries' fast-charging capabilities. Real-world highway consumption values were applied to simulate 1000 km journeys at 120 km/h under cold (−10 °C, cabin heating) and mild (23 °C, no AC) weather scenarios. An optimization model was developed to minimize total trip time by adjusting the number and duration of charging stops, including a 5 min detour for each charging session. Results show that the optimal charging cutoff point consistently emerges around 59% SoC, with a typical deviation of 10, regardless of ambient temperature. Charging beyond 70% SoC is generally inefficient unless dictated by charging station availability. The optimal strategy involves increasing the number of shorter stops—typically every 2–3 h of driving—thereby reducing total trip.

Keywords: battery electric vehicle; DC fast-charging; charging power; charging curve; charging time

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1. Introduction

Promoting the development and implementation of Battery Electric Vehicles (BEVs) is one of the key ongoing measures to transition towards a low-carbon energy model. Despite their many advantages over conventional vehicles, BEVs adoption remains limited due to certain constraints compared to Internal Combustion Engine Vehicles (ICEVs). Their range and battery recharging times are two of the most significant drawbacks of BEVs.

However, the average range of BEVs has more than doubled in the last decade, while recharging times have been significantly reduced over the same period. For these reasons, BEVs can now undertake long trips with minimal time differences compared to ICEVs.

This difference ranges between 11% and 27%, depending on the BEV's range and charging capabilities, with BEVs requiring more time than ICEVs [1,2].

Given that there are enough high-power DC fast chargers along the route, the duration of a long-distance trip in a BEV essentially depends on two factors. On the one hand, it depends on the battery capacity—and therefore the BEV's range—and on the other hand, on the charging power the battery can handle. BEV long-distance trip times are expected to converge with ICEV times as ultra-fast chargers become widely adopted [3]. Users consider overall travel time—which includes both driving time and charging time—more important than the charging duration itself, as they typically stop to rest every 2–3 h during long trips, which can be done at fast-charging stations [4].

Charging power gradually decreases from 30–40% of the battery's State of Charge (SoC) and drops significantly beyond 70–80%. Therefore, stopping charging at 80% SoC instead of reaching 100% significantly reduces total travel time (including charging stops) [3,5]. Additionally, due to undesirable secondary electrochemical reactions, charging above 80% SoC accelerates battery degradation [1,6]. Despite this effect, it is important to mention that Lithium-Ion Phosphate batteries have very constant voltages over most of the SoC. Thereby the estimation of the SoC mostly relies on Coulomb counting the power in and out. This needs frequent recalibration to be correct. Therefore, LFP batteries should be charged to 100% to get the SoC estimation of the BMS recalibrated, as an accurate SoC estimation helps regulate the charging process [7].

Moreover, DC fast charging above 80% SoC prevents the full utilization of the available charging potential at fast-charging stations by reducing charging power and, consequently, charger availability, which may lead to unnecessary waiting times for other users [8,9]. These delays may occur occasionally during peak hours of daily fast-charging station usage and can become significant in exceptional cases, such as during holiday rush hour traffic [10]. They may also be very frequent if the DC fast-charging network is not sufficiently well-developed [11,12].

On the other hand, prolonged DC fast charging over time causes a significant increase in the battery's internal temperature, which, in addition to reducing power delivery, can, in severe cases, lead to internal short circuits that may destroy the battery and even cause explosions [1,13]. Furthermore, it has been proven that high battery temperatures lead to the fragmentation of electrode materials due to thermal expansion mismatch, causing cell destruction and the consequent degradation of the battery [7,14].

It is neither necessary nor sustainable to size BEV batteries based on maximum usage requirements for long trips [3]. In fact, although manufacturers such as NIO and GAC are developing BEVs with ranges exceeding 1000 km, the weight and cost of the required batteries lead to several drawbacks for these vehicles. Notably, these include poorer performance in terms of longitudinal (acceleration and braking) and transverse (cornering) dynamics, a higher Total Cost of Ownership (TCO) compared to vehicles with lower-capacity batteries, and lower energy efficiency [15]. Instead, a more effective approach is to size BEV batteries around 400 km range and design optimal fast-charging strategies that minimize charging sessions and reduce total travel times.

Choosing a DC fast-charging station with a charging power that matches the maximum power the vehicle's battery can handle, along with preconditioning (heating) the battery before charging, can significantly reduce charging times by up to 50% in some cases [1,16,17]. Battery preconditioning is especially important to achieve optimal performance [13] and when performing DC fast charging at very low temperatures [18,19]. Under such conditions, not only does charging efficiency decrease significantly [20], leading to considerably longer charging times [21], but battery degradation also increases, reducing its lifespan [22]. For this reason, most EVs' manufacturers—including Audi, Hyundai,

MG and Tesla—incorporate an automatic preconditioning system when the vehicle’s navigation system sets a DC fast-charging station as the destination.

Considering that the main parameters influencing a battery’s charging session are well known, two key factors play an important role in optimizing battery electric vehicles’ DC fast charging for long-distance trips. The first one is the user, who is usually not aware of the optimal State of Charge (SoC) range that maximizes the charging session’s power. This combined with the fact that most BEV drivers experience the so-called “range anxiety” [23,24], leads to charging the battery outside its optimal SoC window, which can reduce efficiency and increase charging times. For example, a user may stop at a fast-charging station with 30% SoC and charge the battery up to 95%. This would result in a charging session approximately 50% longer compared to a session from 10% to 75% SoC, despite both recovering the same range.

The second parameter is the difference between the charging power curves of each BEV on the market, which varies significantly across different models and brands. This aspect also plays a crucial role in minimizing long-distance trip times. Charging power is higher at low SoC levels and decreases as the charge percentage increases. This trend results from battery management strategies, which aim to accelerate charging when the battery is less charged and reduce it as it approaches higher SoC levels in order to preserve battery health.

This paper analyzes data from a broad sample of BEVs available on the market, based on testing and recording the main parameters of their charging sessions, and establishes the optimal SoC window for maximizing charging power and reducing stop times. The goal is to provide users with practical information to optimize their vehicles’ DC fast-charging sessions for long-distance trips.

2. Materials and Methodology

This section shows the materials that were used to carry out this research and explains the methodology used for obtaining the optimal DC fast-charging strategies for a wide range of battery electric vehicles during long-distance trips.

In order to obtain sufficient data to draw solid conclusions, 62 BEVs from different segments were tested. All tested vehicles are available in the European market. Table 1 shows the number of EVs tested in this research, classified by segment. As can be seen, segments C, D, and E are the most numerous, as these types of vehicles are more likely to be used for long-distance trips. However, segments A, B, F and commercial vehicles were also tested to provide useful information for their respective users.

Table 1. Number of battery electric vehicles tested classified according to their segment.

Segment	Number of BEVs Tested
A (Mini)	2
B (Compact)	8
C (Medium)	14
D (Large)	20
E (Executive)	12
F (Luxury)	3
N (Commercial)	3

High-power DC fast-charging stations, of up to 350 kW, were used in this research to recharge the EVs’ batteries. Choosing the appropriate charging equipment ensured that the EVs’ battery could be charged to its maximum admissible power, avoiding the limitation in the charging speed that could be caused by the charging station. Therefore, DC fast-charging equipment was selected specifically for each vehicle according to their

battery architecture (400 or 800 V) and maximum charging power capabilities. All these charging stations were equipped with CCS Combo 2 connectors, as all tested vehicles were equipped with this type of DC fast-charging port.

The first step in this research was to obtain the fast-charging power (kW) vs. SoC (%) curve for each BEV, since manufacturers usually only provide the maximum DC fast-charging power achievable under ideal conditions. However, this value is not constant throughout the charging session and is typically only reached at the beginning if the battery's SoC is sufficiently low and the battery has been properly pre-conditioned. The fast-charging curve is essential for evaluating the EVs' travel capability and for determining the optimal fast-charging strategy for each vehicle, as it directly affects recharging times [5].

In order to obtain the fast-charging power curves, all BEVs were tested at a high-power DC fast-charging station. To ensure optimal fast-charging conditions, all vehicles equipped with this feature underwent 45 min of battery preconditioning before the charging session began. Charging power, SoC and battery temperature were recorded using both the data provided by the charging station and the information retrieved from each vehicle's Battery Management System (BMS) via the EOBD connector. Data was collected at 1% SoC intervals between 10% and 90% throughout the entire charging session. Figure 1 shows two of the tested vehicles during the tests along with all the data recorded during each fast-charging session.

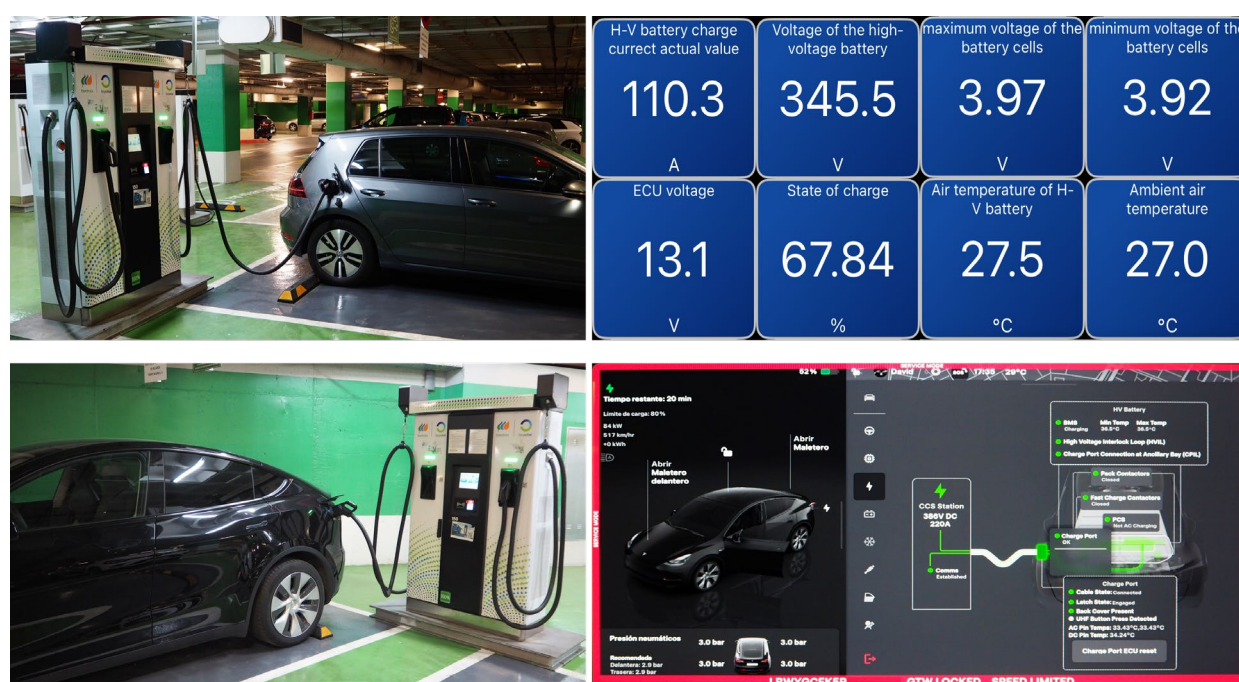


Figure 1. Different battery electric vehicles' DC fast-charging tests.

On the other hand, Figure 2 shows, as a reference, the fast-charging power curves of 4 of the 62 tested vehicles (Audi eTron GT, Tesla Model Y, Toyota bZ4X and Volkswagen eGolf). These vehicles have been chosen as examples to highlight the significant differences in fast-charging power curves among various technologies (i.e., 400 V vs. 800 V battery architectures or passive vs. active thermal management systems). The figure in brackets corresponds to the nominal net capacity of each vehicle's battery, expressed in kWh.

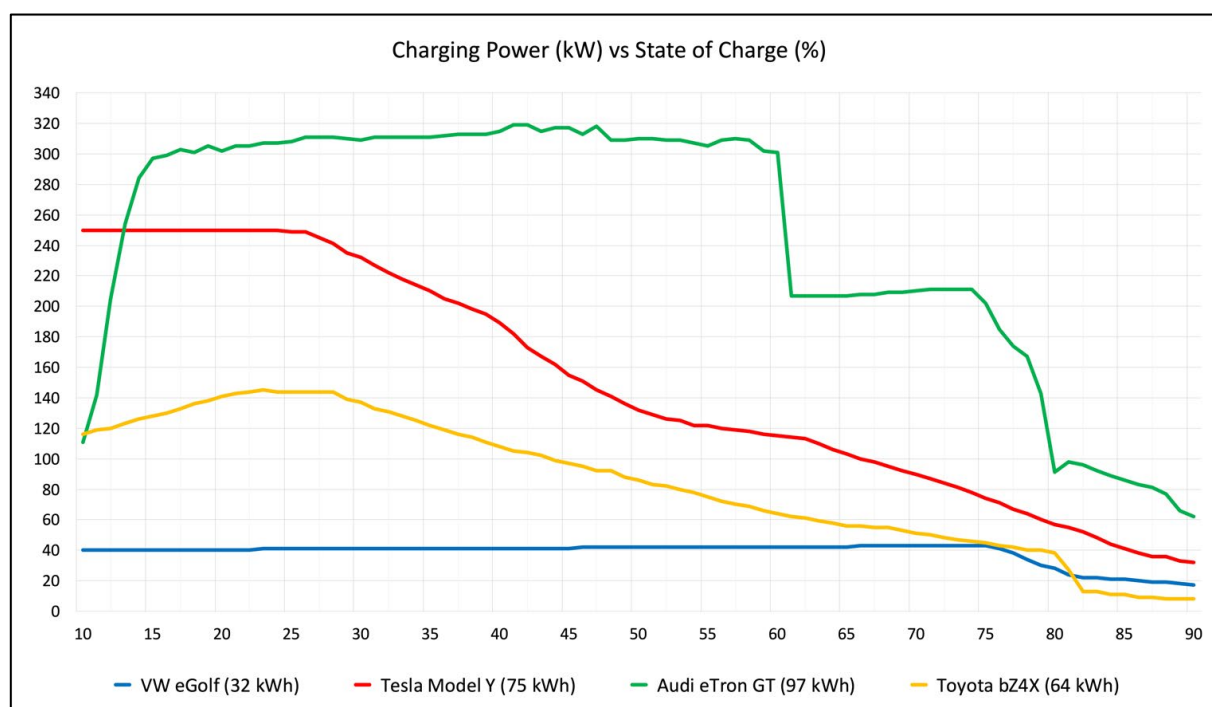


Figure 2. Charging power curves of different BEVs under optimal conditions.

The amount of energy stored in a battery during a charging session depends on the charging power that the battery can handle during this time. In this case, charging power (kW) is plotted against SoC (%), and the area under the curve represents the amount of energy delivered to the battery during charging.

For this reason, fast-charging capabilities do not depend merely on the maximum charging power an EV can reach under ideal conditions, as this level is often maintained only for a short period. Therefore, maintaining a high power level over a wide SoC range is more important in order to recharge the battery faster and more efficiently.

A larger area under the curve corresponds to a greater total amount of energy transferred to the battery. For example, the Audi eTron GT (green line) maintains significantly higher charging power for a longer period compared to the Tesla Model Y (red), Toyota bZ4X (yellow), and VW eGolf (blue), indicating that it can accumulate more energy in a shorter time. Conversely, vehicles with lower power curves accumulate energy more slowly, extending the charging session and, therefore, prolonging long-distance trips.

Moreover, as the battery's fast-charging capabilities depend significantly on its temperature, several vehicles' fast-charging power curves were registered both with the battery being cold and pre-conditioned prior to the charging session. Cold battery temperatures ranged from 8 to 14 °C, while preconditioning was carried out for 45 min prior to fast charging, raising battery temperatures between 41 and 52 °C. This was done to show the influence of battery temperature and pre-conditioning in the batteries' fast-charging capabilities.

Figure 3 shows the difference between the fast-charging power curves of a cold and a preconditioned battery for both a Tesla Model S and a Volvo XC40. As can be seen, the initial charging power of a cold battery can be almost half that of the preconditioned battery. However, both power curves tend to converge over time, as the thermal management system—and the charging process itself—gradually warm up the cold battery. For the same charging duration, a preconditioned battery within the 10% to 50% SoC range can store up to twice the amount of energy as a cold battery. This difference can significantly reduce fast-charging sessions and, consequently, overall long-distance trip times.

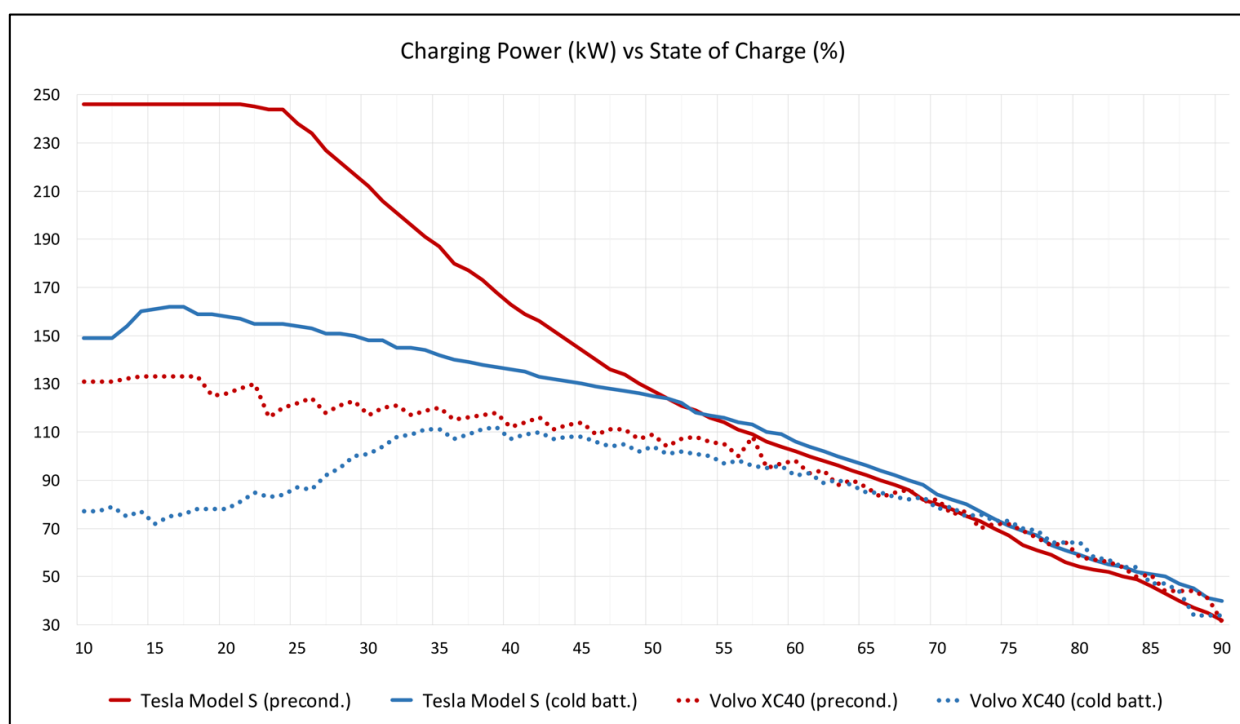


Figure 3. Comparison between charging power curves of cold and preconditioned batteries.

In addition to the fast-charging curve, two other factors play an essential role in an EV's long-distance travel capability. One of them is the battery's net capacity, typically expressed in kWh. This net capacity refers to the usable energy content of the battery, as the actual capacity—known as gross or nominal capacity—is higher but partially unavailable for safety and durability reasons. The difference between the gross and net capacity is called the battery buffer and usually ranges from 5 to 10% of the nominal capacity.

The other factor that influences an EV's long-distance travel capability is its energy consumption at highway speeds, typically measured in Wh/km or kWh/100 km. Although every EV has a standard rated consumption and range, these values vary significantly depending on the standardized test procedure under which the vehicle was tested and type approved. The most common standard test protocols are WLTP [25] for Europe, EPA [26] for the USA, and CLTC [27] for China.

However, the standardized rated consumption of any of these protocols includes a mix of city, interurban, and highway driving. Since EVs tend to have significantly lower energy consumption in city driving—unlike ICE vehicles—the standardized ratings are not representative of real long-distance trips consumption.

For this reason, this research considers actual highway consumption values obtained under real-world conditions, as published by EV Database <https://ev-database.org/> (accessed on 8 March 2025). Moreover, as EV energy consumption can vary considerably (by up to 30%) depending on weather conditions, two scenarios were considered: the first, called Cold Weather, represents a worst-case scenario with an outside temperature of -10°C and cabin heating in use; the second, Mild Weather, represents a best-case scenario with an outside temperature of 23°C and no air conditioning. The low-temperature condition of -10°C was selected because it represents a cold climate in which vehicles are still commonly operated in many countries.

Table 2 below shows the battery specifications and highway energy consumption for a sample of the 62 EVs analysed in this study. The battery net capacity and Mild and Cold Weather highway consumption for each vehicle analyzed in this study are provided in Table A4 of Appendix A.

Table 2. Battery net capacity and Mild and Cold Weather highway consumption of different EVs.

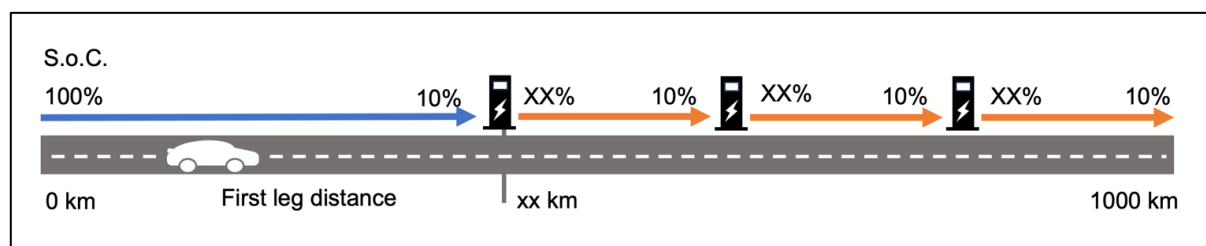
EV Make & Model	Battery Net Cap. (kWh)	Mild Consump. (Wh/km)	Cold Consump. (Wh/km)
Audi eTron GT	97	190	249
Tesla Model Y LR	75	181	234
Toyota bZ4X	64	200	256
VW eGolf	32	188	237

Since most new battery electric vehicles can travel more than 300 km on a single charge, a 1000 km journey at highway speed was considered as long-distance trip. The first leg starts with a fully charged battery (100% SoC), and the first charging stop occurs when the battery charge reaches 10% SoC. The rest of the trip is divided into several charging legs, depending on the vehicle's needs. The time required to recharge the battery from 10% to 90% SoC is calculated for each charging stop based on the vehicle's previously obtained charging power curve, with each subsequent leg also ending at 10% SoC.

To ensure uniform and comparable testing conditions across all vehicles, the following assumptions were established:

- All electric vehicles are assumed to support the Plug & Charge protocol, eliminating any time delays associated with initiating or ending the charging session.
- Charging stations are assumed to consistently supply the power requested by the vehicles' BMS throughout the charging process.
- Battery degradation is not considered: all batteries are assumed to have a State of Health (SoH) of 100%.
- Environmental conditions align with the previously defined "Mild" and "Cold" weather scenarios.
- The assumed traffic conditions and road network enable continuous driving at a constant speed of 120 km/h.

Figure 4 presents an infographic outlining the testing methodology and the procedure used to determine the optimal charging strategy for each vehicle.

**Figure 4.** Testing methodology and procedure to determine the optimal charging strategy.

The real range (in kilometers) of each vehicle is calculated, according to Equation (1), by dividing the battery's net capacity, expressed in kilowatt-hours (kWh), by the vehicle's real energy consumption, expressed in watt-hours per kilometer (Wh/km).

$$\text{Real range (km)} = \frac{\text{Battery net capacity (kWh)} \cdot 1000 \text{ (Wh/kWh)}}{\text{Real consumption (Wh/km)}} \quad (1)$$

On the other hand, the total charging time (in minutes) is equal to the number of charging stops (n) multiplied by the sum of the charging session duration and the detour time, as can be seen in the following Equation (2):

$$\text{Total charging time (min)} = n \cdot (\text{charging session time} + \text{detour time}) \quad (2)$$

After that, the total trip time (in hours) is calculated by adding the total time spent charging to the driving time. The driving time is obtained by dividing the total distance

(1000 km) by the cruising speed (120 km/h). Accordingly, the following Equation (3) is obtained:

$$\text{Total trip time (h)} = \text{Total charging time} + \frac{1000 \text{ km}}{120 \text{ (km/h)}} \quad (3)$$

This results in a driving time of 8.33 h, to which the total charging time must be added to obtain the full trip duration. Then, the minimum number of charging stops is determined by considering the previously calculated real range and the fact that each charging stop occurs when the battery's state of charge (SoC) reaches 10%.

Finally, a MATLAB script calculates the total time required to recharge the battery, considering a range between the minimum number of charging stops and a maximum of 15 stops. It thereby determines the optimal number of stops that minimizes the total charging time—and therefore, the total trip time—under the assumption that there are sufficient fast-charging stations along the route and that each recharge includes a 5 min detour.

3. Results and Analysis

This section presents the key findings of the study for a representative subset of the 62 battery electric vehicles analyzed. Comprehensive results for all tested vehicles are provided in Appendix A, where they are presented in tabular form.

Table 3 presents the top 5, among all 62 EVs, that achieve the largest reductions in total trip time when optimized charging strategies are applied under Mild Weather conditions. For each model, the table compares the minimum number of charging stops required to complete the 1000 km journey with the optimal number of stops derived from the charging power curves and consumption data. The “Time saved” column quantifies the improvement in total recharging time achieved by adopting the optimal strategy. The minimum and optimal charging stops, along with time saved in Mild Weather conditions for each vehicle analyzed in this study, are provided in Table A1 of Appendix A.

Table 3. EVs with the highest time savings from optimized charging strategies in Mild Weather conditions.

EV Make & Model	Minimum Charging Stops		Optimal Charging Stops		Time Saved (min)
	Number of Charging Stops	Total Recharging Time (min)	Number of Charging Stops	Total Recharging Time (min)	
Toyota bZ4X 64 kWh	3	151.40	6	101.67	49.73
Nissan Townstar 45 kWh	6	242.72	9	208.11	34.61
Volvo C40 75 kWh	3	128.06	5	105.02	23.04
Polestar 2 61 kWh	3	125.31	5	104.83	20.48
MG Cyberster 75 kWh	2	94.72	4	78.19	16.53

Under Mild Weather conditions, the Toyota bZ4X (64 kWh) exhibits the largest absolute time saving, reducing total recharging time by approximately 49.73 min when increasing the number of charging stops from three to six, thereby leveraging shorter and more efficient charging sessions. This corresponds to a 32.85% reduction compared to the minimum-stop strategy.

The Nissan Townstar (45 kWh) achieves a total recharging time reduction of 34.61 min, from 242.72 min with six stops to 208.11 min with nine stops, representing a 14.26% improvement. This gain is particularly notable for a small-capacity battery vehicle operating at high fast-charging frequencies.

The Volvo C40 (75 kWh) benefits from a time saving of 23.04 min, achieved by increasing stops from three to five, corresponding to an 18.00% reduction. The Polestar 2 (61

kWh) follows closely, with a 20.48 min reduction (16.33%) when increasing stops from three to five.

Finally, the MG Cyberster (75 kWh) achieves a time saving of 16.53 min (17.45%) by increasing stops from two to four, highlighting that even high-capacity battery EVs can benefit from optimized charging intervals under favorable ambient conditions.

These results indicate that, for most EV models, increasing the frequency of charging stops—thus operating more frequently within the battery’s higher-power charging range—can significantly reduce total recharging time, enhancing long-distance travel efficiency.

On the other hand, Table 4 presents the five best battery electric vehicles achieving the highest time savings by using optimized charging strategies under Cold Weather conditions. As in Table 3 (Mild Weather conditions), the results indicate that increasing the number of charging stops—thereby maintaining the battery within a higher charging power range—can significantly reduce total recharging time. However, the magnitude of time savings in cold conditions is substantially greater due to the more pronounced negative impact of low temperatures on energy consumption and charging performance. The minimum and optimal charging stops, along with time saved in Cold Weather conditions for each vehicle analyzed in this study, are provided in Table A2 of Appendix A.

Table 4. EVs with the highest time savings from optimized charging strategies in Cold Weather conditions.

EV Make & Model	Minimum Charging Stops		Optimal Charging Stops		Time Saved (min)
	Number of Charging Stops	Total Recharging Time (min)	Number of Charging Stops	Total Recharging Time (min)	
Toyota bZ4X 64 kWh	4	257.24	8	141.24	116.00
Nissan Townstar 45 kWh	7	394.93	10	289.57	105.36
Polestar 2 61 kWh	4	199.49	8	149.61	49.88
Volvo C40 75 kWh	4	187.23	7	145.54	41.69
Hyundai Inster 46 kWh	5	211.45	6	176.00	35.45

Under Cold Weather conditions, absolute time savings are markedly higher due to the higher energy consumption and reduced charging power at low temperatures. The Toyota bZ4X (64 kWh) achieves the greatest improvement, reducing total recharging time by 116.00 min (45.09%) when increasing stops from four to eight.

The Nissan Townstar (45 kWh) records a 105.36 min saving (26.68%) when increasing stops from seven to ten. This result underscores the significant impact of optimization in small-battery vehicles affected by low-temperature charging limitations.

The Polestar 2 (61 kWh) achieves a 49.88 min reduction (25.01%) when increasing stops from four to eight, while the Volvo C40 (75 kWh) shows a 41.69 min saving (22.27%) with an increase from four to seven stops.

The Hyundai Inster (46 kWh) records the smallest absolute gain in this set, with a 35.45 min reduction (16.77%) when increasing stops from five to six, reflecting the influence of both battery size and charging profile on optimization outcomes.

A cross-comparison of Tables 3 and 4 reveals that Cold Weather conditions amplify the absolute benefits of optimal charging strategies, with time savings more than doubling for the top performers compared to Mild Weather. For example, the Toyota bZ4X increases its absolute gain from 49.73 min to 116.00 min, and the Nissan Townstar from 34.61 min to 105.36 min. This disparity is primarily attributed to the higher energy consumption at low temperatures, and the lower charging power attainable at reduced battery temperatures, which prolongs each individual charging session; thus, breaking recharging into more frequent but shorter sessions mitigates the overall time penalty.

Figure 5 synthesizes the time-saving performance, in minutes, of the vehicles listed in Tables 3 and 4, providing a direct visual comparison between Mild and Cold Weather scenarios. The bar plots highlight the substantial increase in absolute time savings under Cold Weather conditions across all models, confirming the trends identified in the tabular analysis. Notably, the Toyota bZ4X and Nissan Townstar display the most pronounced improvements, while vehicles with larger battery capacities such as the Volvo C40 and MG Cyberster show more moderate, though still significant, gains. This visualization underscores the importance of adapting charging strategies to environmental conditions in order to minimize total travel time during long-distance trips.

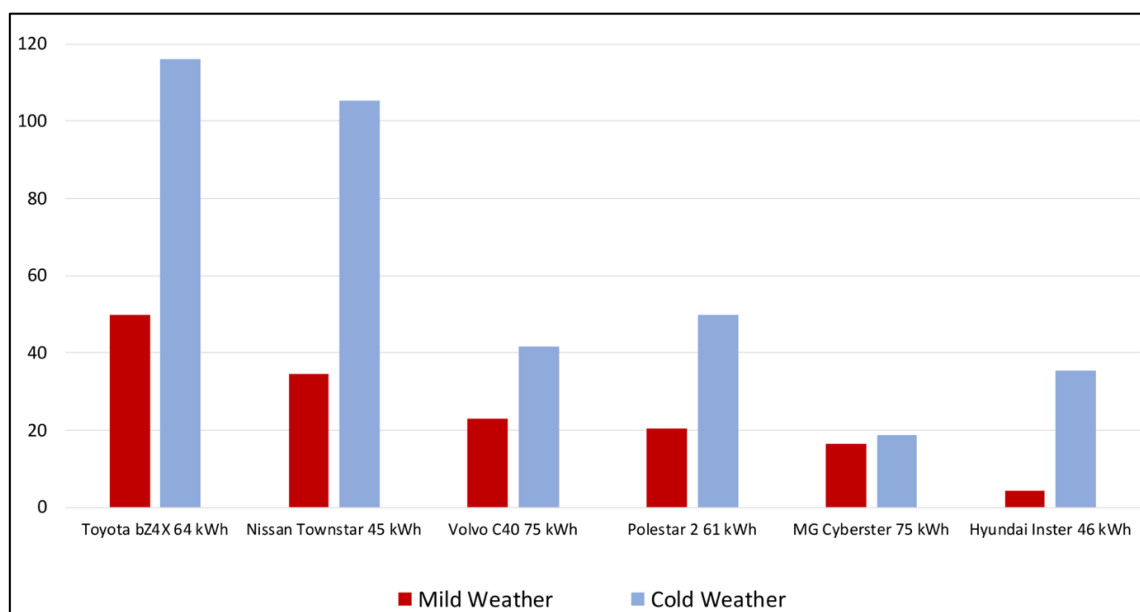


Figure 5. Time saved (min) between the minimum and the optimal charging stops strategies.

On the other hand, Figure 6 illustrates the distribution of the optimal number of charging stops for the 62 EVs analyzed in this study, comparing Mild and Cold Weather scenarios. Under Mild Weather conditions, the optimal strategy typically involves between 3 and 5 charging stops, with the majority of vehicles clustering around 3 and 4 stops. By contrast, Cold Weather conditions lead to a systematic increase in the number of optimal stops, with most EVs requiring between 4 and 7 charging events. Notably, the mean value shifts from 3.94 stops in Mild Weather to 5.48 stops in Cold Weather, with several vehicles even exceeding 8 stops when operating under adverse thermal conditions.

These aggregated results complement the findings presented in Tables 3 and 4, where individual vehicle case studies highlighted significant time savings achieved through optimized charging strategies. While Tables 3 and 4 demonstrated the magnitude of time reduction for specific EVs, Figure 6 generalizes these observations by showing how colder climates consistently increase the number of required charging stops. Taken together, the results confirm that Cold Weather not only extends charging times, but also alters the optimal trip planning strategy, thereby reinforcing the role of thermal management and battery preconditioning in mitigating performance losses.

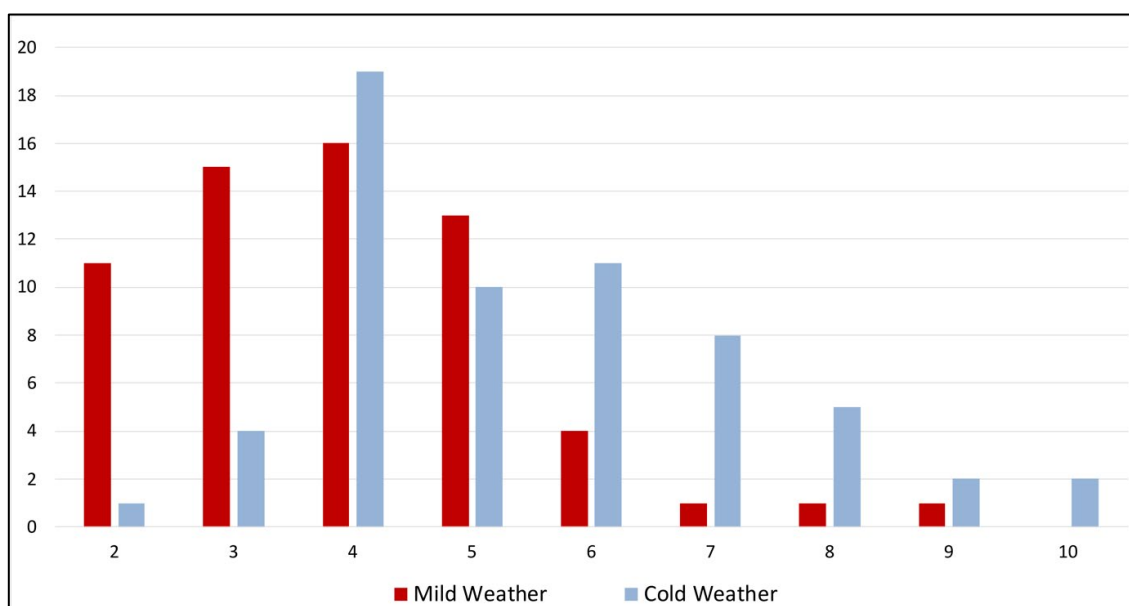


Figure 6. Optimal number of charging stops under Mild and Cold Weather conditions.

Finally, the research determined an optimal mean SoC cutoff point of 58.7% under Mild Weather conditions and 59.6% under Cold Weather conditions, with a standard deviation of 10.1 and 10.4, respectively. These findings provide valuable guidance for EV users seeking to optimize long-distance trip times, as they indicate that charging beyond 70% SoC is generally not advantageous unless specific factors—such as the distance to the next fast-charging station—require it. The optimal SoC cutoff point for each vehicle analyzed in this study, under Mild and Cold Weather conditions, is provided in Table A3 of Appendix A.

4. Discussion

The results obtained in this research demonstrate that the optimization of charging strategies has a significant impact on long-distance travel times for EVs. The analysis of 62 vehicles from different market segments revealed that an optimal charging cutoff point consistently appears around 59% SoC, regardless of weather conditions, although with a typical deviation of approximately 10. Furthermore, the comparison between Mild and Cold Weather scenarios shows that low ambient temperatures not only extend charging times due to reduced power intake and higher consumption, but also increase the number of optimal charging stops, as illustrated in Figure 6. This highlights the critical influence of environmental conditions and battery thermal management on EV usability for long-distance trips.

These findings are consistent with prior works that emphasize the non-linearity of EV charging curves and the detrimental effects of cold temperatures on charging efficiency and energy consumption. Previous studies have reported efficiency penalties of 20–40% under cold climates, which aligns with the time extensions and additional charging stops observed in this research. However, the present study contributes a novel quantitative assessment of optimal cutoff SoC values and their statistical dispersion across a large and diverse EV sample, providing practical thresholds that have not been systematically reported in earlier literature. In particular, the integration of fast-charging curves with real-world consumption data strengthens the external validity of the results compared to standardized WLTP or EPA values, which are known to underestimate highway consumption.

For industry stakeholders, these results underscore the importance of developing advanced thermal management systems and offering predictive route planners that incorporate weather and charging infrastructure availability, according to the vehicle's fast-charging capability, to optimize trip planning. Furthermore, vehicle software should be designed to notify users of the optimal point at which to end a charging session and continue to the next available charging station, thereby facilitating the adoption of efficient charging strategies in real-world scenarios.

5. Conclusions

The results have shown an optimal charging cutoff point much before 80% State of Charge, which is the typical manufacturer's recommendation. This finding indicates that, in general, charging beyond 65% SoC is inefficient for minimizing trip duration, unless dictated by station availability constraints. Moreover, low ambient temperatures have demonstrated to increase the number of optimal charging stops. For both reasons, the optimal strategy is to increase the number of stops while keeping them shorter, generally every 2–3 h of driving.

From a user perspective, the results provide actionable insights for planning long-distance trips. By adopting charging strategies that stop sessions around 60–70% SoC and increasing the number of short, high-power sessions, drivers can reduce overall travel times by up to 30 to 40% under favourable conditions. In colder climates, preconditioning emerges as a key enabler, mitigating the otherwise severe penalties on charging efficiency.

Despite the robustness of the findings, certain limitations must be acknowledged. Firstly, the analysis assumes ideal charging infrastructure availability, whereas in real-world scenarios station occupancy, detours, and charging power fluctuations may alter the optimal strategies. Secondly, the study focused on highway driving at a constant speed of 120 km/h, which may not capture the full variability of on-road driving conditions. Additionally, the results are based on data from currently available EVs; future models with higher charging capabilities or larger battery capacities may shift the identified optimal cutoff point. Future research should therefore integrate dynamic traffic simulations, station availability models, and seasonal energy mix assessments to provide a more comprehensive evaluation of EV long-distance travel feasibility.

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Appendix A

Table A1. Minimum and optimal charging stops and time saved in Mild Weather conditions.

EV Make & Model	Minimum Charging Stops			Optimal Charging Stops			Time Saved (min)
	No. of Charging Stops	Total Re-charging Time (min)	Total Travel Time (h)	No. of Charging Stops	Total Re-charging Time (min)	Total Travel Time (h)	
Audi e-tron GT 105 kWh	2	32.27	8.87	2	32.27	8.87	0.00
Audi Q6 e-tron 100 kWh	2	50.32	9.17	3	49.19	9.15	1.13
Audi Q4 e-tron 82 kWh	3	73.78	9.56	4	70.00	9.50	3.78
BMW i3 42 kWh	5	213.81	11.90	5	213.81	11.90	0.00
BMW i4	2	50.90	9.18	3	49.35	9.16	1.55
BMW i7 105 kWh	2	51.43	9.19	2	51.43	9.19	0.00
BMW iX3	3	90.18	9.84	4	87.26	9.79	2.92
BYD Dolphin 60 kWh	3	146.24	10.77	4	144.20	10.74	2.04
BYD Seal 84 kWh	2	71.04	9.52	4	64.43	9.41	6.61
BYD Seal U 89 kWh	3	110.89	10.18	6	102.03	10.03	8.86
BYD Sealion 7 93 kWh	3	77.47	9.62	3	77.47	9.62	0.00
Citroen e-C4X 54 kWh	3	107.72	10.13	4	100.14	10.00	7.58
Citroen e-Spacetourer 75 kWh	5	207.80	11.80	5	207.80	11.80	0.00
Ford Explorer 82 kWh	3	62.17	9.37	3	62.17	9.37	0.00
Ford Mustang Mach-e GT	3	118.68	10.31	5	117.10	10.29	1.58
Hyundai Instert 49 kWh	4	132.30	10.54	5	128.10	10.47	4.20
Hyundai Ioniq 28 kWh	6	171.19	11.19	7	157.06	10.95	14.13
Hyundai Ioniq 6 77 kWh	2	39.06	8.98	2	39.06	8.98	0.00
Hyundai Kona 65 kWh	3	106.45	10.11	4	100.87	10.01	5.58
Kia EV3 81 kWh	2	84.45	9.74	3	73.67	9.56	10.78
Kia Niro EV 64 kWh	3	135.16	10.59	4	128.47	10.47	6.69
Kia EV9 100 kWh	2	75.24	9.59	3	62.72	9.38	12.52
Kia Niro EV 64 kWh	3	126.75	10.45	4	122.22	10.37	4.53
Mercedes EQA 250+ 74 kWh	3	91.69	9.86	3	91.69	9.86	0.00
Mercedes EQE	2	72.51	9.54	3	66.42	9.44	6.09
Mercedes EQS 120 kWh	1	36.56	8.94	2	35.62	8.93	0.94
MG4 64 kWh	3	94.16	9.90	4	83.35	9.72	10.81
MG ZS EV 72 kWh	3	129.02	10.48	4	125.82	10.43	3.20
MG Marvel R 70 kWh	3	151.32	10.86	4	141.05	10.68	10.27
MG Cyberster 77 kWh	2	94.72	9.91	4	78.19	9.64	16.53
Nio EL6 100 kWh	2	80.29	9.67	3	78.89	9.65	1.40
Nio EL8 100 kWh	2	61.49	9.36	3	56.31	9.27	5.18
Nio ET5 100 kWh	2	80.24	9.67	2	80.24	9.67	0.00
Nissan Ariya 63 kWh	4	117.58	10.29	5	116.62	10.28	0.96
Nissan Ariya 87 kWh	2	89.08	9.82	3	86.97	9.78	2.11
Nissan Townstar 45 kWh	6	242.72	12.38	9	208.11	11.80	34.61
Polestar 2 64 kWh	3	125.31	10.42	5	104.83	10.08	20.48
Polestar 2 refresh 82 kWh	2	59.86	9.33	3	56.22	9.27	3.64
Polestar 4 100 kWh	2	60.58	9.34	2	60.58	9.34	0.00
Porsche Taycan 93 kWh	2	54.44	9.24	3	53.48	9.22	0.96
Renault Zoe 52 kWh	4	218.85	11.98	5	214.69	11.91	4.16
Renault Megane 60 kWh	3	110.07	10.17	6	100.50	10.01	9.57
Renault Scenic 92 kWh	2	80.22	9.67	3	77.46	9.62	2.76

Tesla M3 RWD Highland	2	74.75	9.58	4	62.04	9.37	12.71
Tesla Model 3 LR 80 kWh	2	35.56	8.93	2	35.56	8.93	0.00
Tesla Model Y RWD BYD	3	77.26	9.62	4	73.50	9.56	3.76
Tesla Model Y LR LG	2	79.93	9.67	4	65.37	9.42	14.56
Tesla Model S P85 2013	3	117.62	10.29	5	109.23	10.15	8.39
Tesla Model S LR 2023	2	37.64	8.96	2	37.64	8.96	0.00
Toyota bZ4X	3	151.40	10.86	6	101.67	10.03	49.73
Volvo C40 78 kWh	3	128.06	10.47	5	105.02	10.08	23.04
Volvo EX30 69 kWh	3	103.54	10.06	5	90.64	9.84	12.90
Volvo XC40 69 kWh	4	113.73	10.23	5	112.65	10.21	1.08
VW ID Buzz 82 kWh	3	116.06	10.27	6	106.86	10.11	9.20
VW e-Golf 36 kWh	7	275.42	12.92	8	274.90	12.92	0.52
VW ID3 Facelift 62 kWh	3	120.21	10.34	5	105.21	10.09	15.00
VW ID4 82 kWh	3	95.42	9.92	4	92.21	9.87	3.21
VW ID5 GTX 82 kWh	3	90.44	9.84	5	84.90	9.75	5.54
VW ID7 82 kWh	2	55.45	9.26	3	50.55	9.18	4.90
Xpeng P7	2	99.06	9.98	2	99.06	9.98	0.00
Xpeng G6 92 kWh	2	48.71	9.15	2	48.71	9.15	0.00
Xpeng G9 98 kWh	2	46.29	9.10	2	46.29	9.10	0.00

Table A2. Minimum and optimal charging stops and time saved in Cold Weather conditions.

EV Make & Model	Minimum Charging Stops			Optimal Charging Stops			Time Saved (min)
	No. of Charging Stops	Total Re-charging Time (min)	Total Travel Time (h)	No. of Charging Stops	Total Re-charging Time (min)	Total Travel Time (h)	
Audi e-tron GT 105 kWh	3	50.62	9.18	3	50.62	9.18	0.00
Audi Q6 e-tron 100 kWh	3	70.98	9.52	4	69.91	9.50	1.07
Audi Q4 e-tron 82 kWh	4	107.22	10.12	6	100.60	10.01	6.62
BMW i3 42 kWh	7	295.64	13.26	7	295.64	13.26	0.00
BMW i4	3	79.45	9.66	4	76.00	9.60	3.45
BMW i7 105 kWh	3	78.05	9.63	3	78.05	9.63	0.00
BMW iX3	4	131.35	10.52	5	122.41	10.37	8.94
BYD Dolphin 60 kWh	4	211.65	11.86	5	201.21	11.69	10.44
BYD Seal 84 kWh	3	107.78	10.13	5	96.94	9.95	10.84
BYD Seal U 89 kWh	3	162.12	11.04	9	140.95	10.68	21.17
BYD Sealion 7 93 kWh	3	127.03	10.45	4	106.95	10.12	20.08
Citroen e-C4X 54 kWh	5	149.37	10.82	6	144.63	10.74	4.74
Citroen e-Spacetourer 75 kWh	6	278.13	12.97	7	272.19	12.87	5.94
Ford Explorer 82 kWh	3	98.43	9.97	5	90.11	9.84	8.32
Ford Mustang Mach-e GT	3	191.93	11.53	7	164.22	11.07	27.71
Hyundai Inster 49 kWh	5	211.45	11.86	6	176.00	11.27	35.45
Hyundai Ioniq 28 kWh	9	217.77	11.96	9	217.77	11.96	0.00
Hyundai Ioniq 6 77 kWh	3	61.58	9.36	4	60.94	9.35	0.64
Hyundai Kona 65 kWh	4	160.87	11.01	5	142.19	10.70	18.68
Kia EV3 81 kWh	3	119.13	10.32	4	105.70	10.10	13.43
Kia Niro EV 64 kWh	4	194.58	11.58	6	181.11	11.35	13.47
Kia EV9 100 kWh	3	93.66	9.89	4	87.50	9.79	6.16
Kia Niro EV 64 kWh	4	184.41	11.41	6	174.23	11.24	10.18
Mercedes EQA 250+ 74 kWh	4	132.43	10.54	4	132.43	10.54	0.00
Mercedes EQE	3	102.17	10.04	4	95.50	9.92	6.67
Mercedes EQS 120 kWh	2	58.89	9.31	2	58.89	9.31	0.00

MG4 64 kWh	4	139.43	10.66	6	117.30	10.29	22.13
MG ZS EV 72 kWh	4	186.05	11.43	5	174.75	11.25	11.30
MG Marvel R 70 kWh	4	224.36	12.07	6	196.33	11.61	28.03
MG Cyberster 77 kWh	3	132.35	10.54	5	113.54	10.23	18.81
Nio EL6 100 kWh	3	109.37	10.16	3	109.37	10.16	0.00
Nio EL8 100 kWh	3	82.84	9.71	4	79.70	9.66	3.14
Nio ET5 100 kWh	3	120.01	10.33	3	120.01	10.33	0.00
Nissan Ariya 63 kWh	5	164.73	11.08	6	160.85	11.01	3.88
Nissan Ariya 87 kWh	3	127.96	10.47	4	125.35	10.42	2.61
Nissan Townstar 45 kWh	7	394.93	14.92	10	289.57	13.16	105.36
Polestar 2 64 kWh	4	199.49	11.66	8	149.61	10.83	49.88
Polestar 2 refresh 82 kWh	3	90.32	9.84	4	84.66	9.74	5.66
Polestar 4 100 kWh	3	89.18	9.82	4	88.64	9.81	0.54
Porsche Taycan 93 kWh	3	80.90	9.68	4	78.66	9.64	2.24
Renault Zoe 52 kWh	5	317.62	13.63	7	300.44	13.34	17.18
Renault Megane 60 kWh	4	163.15	11.05	8	144.04	10.73	19.11
Renault Scenic 92 kWh	3	118.62	10.31	4	114.69	10.24	3.93
Tesla M3 RWD Highland	3	115.21	10.25	5	93.85	9.90	21.36
Tesla Model 3 LR 80 kWh	3	58.41	9.31	4	56.89	9.28	1.52
Tesla Model Y RWD BYD	4	115.49	10.26	5	104.75	10.08	10.74
Tesla Model Y LR LG	3	115.09	10.25	6	96.01	9.93	19.08
Tesla Model S P85 2013	4	170.19	11.17	7	154.45	10.91	15.74
Tesla Model S LR 2023	2	75.33	9.59	4	60.07	9.33	15.26
Toyota bZ4X	4	257.24	12.62	8	141.24	10.69	116.00
Volvo C40 78 kWh	4	187.23	11.45	7	145.54	10.76	41.69
Volvo EX30 69 kWh	4	155.90	10.93	7	128.59	10.48	27.31
Volvo XC40 69 kWh	5	156.23	10.94	6	151.72	10.86	4.51
VW ID Buzz 82 kWh	4	155.85	10.93	8	143.10	10.72	12.75
VW e-Golf 36 kWh	9	363.69	14.39	10	356.48	14.27	7.21
VW ID3 Facelift 62 kWh	4	174.29	11.24	8	148.48	10.81	25.81
VW ID4 82 kWh	4	137.39	10.62	6	130.58	10.51	6.81
VW ID5 GTX 82 kWh	4	130.71	10.51	7	119.89	10.33	10.82
VW ID7 82 kWh	3	84.08	9.73	5	77.47	9.62	6.61
Xpeng P7	3	152.70	10.88	4	149.63	10.83	3.07
Xpeng G6 92 kWh	3	72.13	9.54	4	71.37	9.52	0.76
Xpeng G9 98 kWh	3	67.10	9.45	4	66.86	9.45	0.24

Table A3. Optimal SoC (%) cutoff point under Mild and Cold Weather conditions.

EV Make & Model	Mild Weather	Cold Weather
Audi e-tron GT 105 kWh	62.9	65.6
Audi Q6 e-tron 100 kWh	56.6	59.9
Audi Q4 e-tron 82 kWh	52.4	50.6
BMW i3 42 kWh	84.9	83.8
BMW i4	48.1	54.2
BMW i7 105 kWh	67.3	67.8
BMW iX3	58.8	64.7
BYD Dolphin 60 kWh	66.8	73.7
BYD Seal 84 kWh	42.3	49.2
BYD Seal U 89 kWh	38.3	36.4
BYD Sealion 7 93 kWh	64.3	66.9
Citroen e-C4X 54 kWh	66.7	64.6

Citroen e-Spacetourer 75 kWh	79.1	74.5
Ford Explorer 82 kWh	63.5	56.4
Ford Mustang Mach-e GT	43.9	43.9
Hyundai Inster 49 kWh	65.9	74.3
Hyundai Ioniq 28 kWh	76.7	82.1
Hyundai Ioniq 6 77 kWh	71.1	57.8
Hyundai Kona 65 kWh	57.8	64.8
Kia EV3 81 kWh	59.5	64.4
Kia Niro EV 64 kWh	60.9	58.0
Kia EV9 100 kWh	61.3	64.3
Kia Niro EV 64 kWh	58.1	55.7
Mercedes EQA 250+ 74 kWh	66.5	70.8
Mercedes EQE	60.2	64.5
Mercedes EQS 120 kWh	47.1	72.6
MG4 64 kWh	63.3	60.4
MG ZS EV 72 kWh	63.3	69.0
MG Marvel R 70 kWh	64.3	60.5
MG Cyberster 77 kWh	50.0	56.5
Nio EL6 100 kWh	63.3	85.9
Nio EL8 100 kWh	62.2	65.6
Nio ET5 100 kWh	72.8	72.6
Nissan Ariya 63 kWh	58.7	65.9
Nissan Ariya 87 kWh	61.2	65.7
Nissan Townstar 45 kWh	55.6	65.4
Polestar 2 64 kWh	54.6	49.8
Polestar 2 refresh 82 kWh	55.1	60.9
Polestar 4 100 kWh	75.1	58.0
Porsche Taycan 93 kWh	57.7	63.4
Renault Zoe 52 kWh	62.0	62.0
Renault Megane 60 kWh	42.5	45.0
Renault Scenic 92 kWh	55.9	61.1
Tesla Model 3 RWD Highland	49.2	57.7
Tesla Model 3 LR 80 kWh	60.3	50.8
Tesla Model Y RWD BYD	64.5	72.0
Tesla Model Y LR LG	47.8	47.0
Tesla Model S P85 2013	45.2	45.6
Tesla Model S LR 2023	56.1	47.0
Toyota bZ4X	47.1	48.8
Volvo C40 78 kWh	53.6	53.1
Volvo EX30 69 kWh	52.6	53.2
Volvo XC40 69 kWh	59.8	65.9
VW ID Buzz 82 kWh	49.5	49.7
VW e-Golf 36 kWh	72.2	75.1
VW ID3 Facelift 62 kWh	52.7	47.7
VW ID4 82 kWh	54.1	51.5
VW ID5 GTX 82 kWh	45.2	45.6
VW ID7 82 kWh	54.0	49.9
Xpeng P7	72.6	57.9
Xpeng G6 92 kWh	77.6	60.1
Xpeng G9 98 kWh	78.9	60.0

Table A4. Battery net capacity and Mild and Cold Weather highway consumption of all tested EVs.

EV Make & Model	Battery Net Cap. (kWh)	Mild Consump. (Wh/km)	Cold Consump. (Wh/km)
Audi e-tron GT 105 kWh	97	190	249
Audi Q6 e-tron 100 kWh	94.9	218	275
Audi Q4 e-tron 82 kWh	77	200	257
BMW i3 42 kWh	37.9	176	230
BMW i4	81.3	166	217
BMW i7 105 kWh	101.7	208	268
BMW iX3	74	211	269
BYD Dolphin 60 kWh	60.5	192	247
BYD Seal 84 kWh	82.5	181	236
BYD Seal U 89 kWh	87	226	285
BYD Sealion 7 93 kWh	91.3	231	290
Citroen e-C4X 54 kWh	50.8	161	212
Citroen e-Spacetourer 75 kWh	68	296	368
Ford Explorer 82 kWh	77	193	248
Ford Mustang Mach-e GT	91	236	298
Hyundai Inster 49 kWh	46	170	219
Hyundai Ioniq 28 kWh	28	156	207
Hyundai Ioniq 6 77 kWh	74	157	208
Hyundai Kona 65 kWh	65.4	184	238
Kia EV3 81 kWh	78	186	240
Kia Niro EV 64 kWh	64	188	242
Kia EV9 100 kWh	96	234	295
Kia Niro EV 64 kWh	64.8	183	236
Mercedes EQA 250+ 74 kWh	70.5	183	235
Mercedes EQE	90.6	218	279
Mercedes EQS 120 kWh	107.8	177	232
MG4 64 kWh	61.7	187	242
MG ZS EV 72 kWh	68.3	207	263
MG Marvel R 70 kWh	70	215	275
MG Cyberster 77 kWh	74.4	186	240
Nio EL6 100 kWh	90	225	286
Nio EL8 100 kWh	90	222	281
Nio ET5 100 kWh	90	194	250
Nissan Ariya 63 kWh	63	210	268
Nissan Ariya 87 kWh	87	212	272
Nissan Townstar 45 kWh	45	225	290
Polestar 2 64 kWh	61	191	249
Polestar 2 refresh 82 kWh	79	178	232
Polestar 4 100 kWh	94	207	265
Porsche Taycan 93 kWh	83.7	195	254
Renault Zoe 52 kWh	52	182	236
Renault Megane 60 kWh	60	171	222
Renault Scenic 92 kWh	87	198	256
Tesla Model 3 RWD Highland	57.5	142	189
Tesla Model 3 LR 80 kWh	75	143	190
Tesla Model Y RWD BYD	57.5	177	230
Tesla Model Y LR LG	75	181	234

Tesla Model S P85 2013	80.8	215	274
Tesla Model S LR 2023	95	173	226
Toyota bZ4X	64	200	256
Volvo C40 78 kWh	75	231	294
Volvo EX30 69 kWh	64	194	251
Volvo XC40 69 kWh	67	227	285
VW ID Buzz 82 kWh	77	252	314
VW e-Golf 36 kWh	32	188	237
VW ID3 Facelift 62 kWh	59	179	231
VW ID4 82 kWh	77	205	261
VW ID5 GTX 82 kWh	77	205	261
VW ID7 82 kWh	77	171	223
Xpeng P7	82.7	178	233
Xpeng G6 92 kWh	87.5	197	254
VW eGolf	32	188	237

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