

EV CHARGE – An ICCT model assessing charging infrastructure needs for light-duty electric vehicles

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Executive Summary

Achieving widespread adoption of electric vehicles is contingent upon efficiently deploying the appropriate charging infrastructure at the right pace and location. Identifying the amount, type, and location of public and private charging infrastructure needed is a complex task. The ICCT is thus developing EV CHARGE: a Python-based model to assess charging infrastructure needs for light-duty vehicles (2 and 3 wheelers, passenger cars, and light commercial vehicles) at any given scale: from local (e.g. city district level) to supra-national (e.g. European Union level), for any market and at any time horizon, based on a list of required inputs. This model is an asset to streamline and standardize charging needs assessment analyses. After describing the motivation for deploying such a model, the authors outline the methodology and present the data inputs and outputs. Finally, a case study on Zero Emission Vehicle Transition Council (ZEVTC) jurisdictions is presented.

Keywords: BEV (battery electric vehicle), charger, energy, modeling, strategy

1 Introduction and Background

To keep pace with rapidly growing electric vehicle demand, governments and private sector agree that appropriate buildout of public and private charging infrastructure is needed. However, identifying the right amount, type, and location of both public and private charging infrastructure needed at different time horizons is challenging. Substantial investment in charging infrastructure requires careful planning and time, and it is imperative that governments and all other stakeholders set out expansion targets and strategies well in advance. [1]

This EV CHARGE (Electric Vehicle CHarging and Refueling GEnerator) model is intended to be a valuable resource for governments and all other stakeholders (NGOs, private sector such as charge point operators, businesses, etc.) to have a better understanding of the ecosystem. It can help set goals in terms of the absolute number of chargers needed by type and in terms of installed power output per EV (a new metric in discussion at the European

Union level with the AFIR regulation [2]) and can inform policy-making. This model can also allow policy makers to ensure their jurisdiction is on track to reach their electrification goals.

2 Methodology

This Python-based model can be used to assess any jurisdiction’s EV charging infrastructure needs for different light-duty vehicle types and segments. The vehicle types are 2-3 wheelers, passenger cars, and light commercial vehicles. The segments are a flexible sub-division of vehicle types and can include private vs company cars, with a potential further split by company name or business type, taxis, ride-hailing vehicles, etc.

A jurisdiction can be as large as an entire market (e.g. the European Union) and as small as a city district (e.g., Charlottenburg, Berlin, Germany). Theoretically, the model can work at any level based on data provided by the user (e.g. it would be possible to have a 1 km x 1km grid granularity). However, it is rare to get reliable data for smaller than city district levels. The model will not provide the exact location (latitude and longitude) of each charger but rather the total number of chargers of a given type (for example public destination AC, 11kW) for a given jurisdiction (city district, for example) and a given year. The user can then work with the municipality to identify the potential locations of these chargers based on land availability and grid constraints, among other factors.

The different charger needs assessed fall under two main categories: private and public. These categories are further split by **location**: home, depot, workplace, public overnight, public destination, and en-route (highway) and optionally by **sub-location**: for example, destination – dedicated to taxis, then by **type**: Level 1, Level 2, DC fast, and battery swapping, and finally by **capacity** (for example Level 2 can be further split by 3.7kW, 7.4kW, 11kW, and 22kW).

Two different methodologies are used in the model: an energy-based and a minimum coverage one. Each is better suited for certain charger types and locations as presented in the Table below. For some types of chargers, the number of chargers needed depends less on the annual energy they need to deliver than on a minimum coverage as a function of the maximum distance between stations, the number of vehicles, or the population.

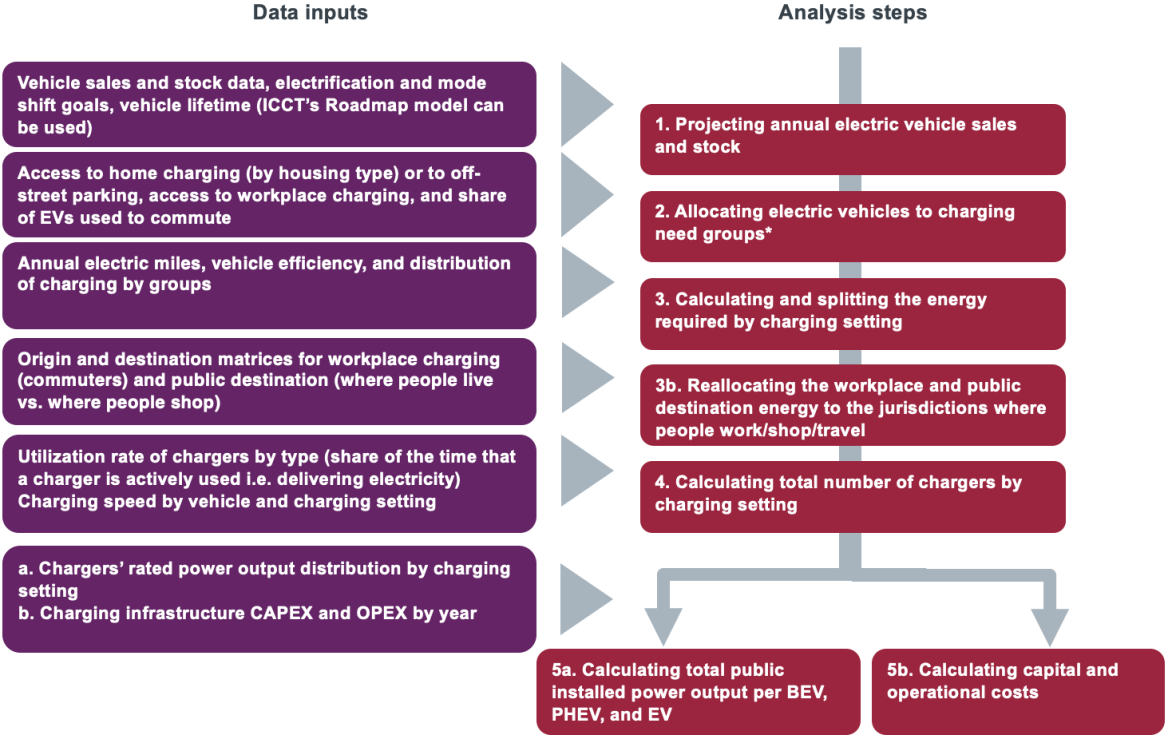
Table 1. Methodology options for different charger locations.

Chargers’ location		Energy-based methodology	Minimum coverage methodology		
			Based on the number of vehicles	Distance-based	Population-based
Private	Home	No	Yes – Default	No	No
	Depot	Optional	Yes – Default	No	No
	Workplace	Yes – Default	No	No	No
Public	Overnight	Yes – Default	No	No	Optional
	Destination	Yes – Default	No	No	Optional
	En-route	Optional	Optional	Yes – Default	No

2.1 Energy-based

This methodology, presented in Figure 1, is best suited for the assessment of public overnight and destination, and private workplace charging. The purple rectangles are the data inputs for

each step, represented by the red rectangles. This methodology is applied for every year and every jurisdiction of the analysis.



* **Charging need group** = regrouping vehicles with the same characteristics and charging patterns. For example, a group could be composed of long-range BEVs used to commute to work and with access to home and workplace charging.

Figure 1. Energy-based charging infrastructure modeling for light-duty vehicles.

The following sections will provide information on each analysis step.

2.1.1 Projecting annual electric vehicle sales and stock

The model starts with the projection of annual electric vehicle sales, which allows us to track BEV and PHEV stock over time based on a stock turnover model. To estimate the number of EVs on the road for every year of the analysis, several data inputs are needed. These include historical data on vehicle lifetime, sales and stock by power type and segments, data on electrification targets, mode shift goals, and any other policies of the jurisdictions analyzed that might have an impact on these inputs.

2.1.2 Allocating electric vehicles to charging needs groups

The next step allocates this EV stock to EV owner groups for each year of the analysis. EVs in one group have similar charging behaviors.

For passenger cars, at a minimum, EVs are split into groups depending on the vehicle powertrain (BEV vs. PHEV), home charging availability, commuting status (car commuter vs. non-car commuter), and workplace charging availability.

For light commercial vehicles (LCVs), at a minimum, EVs are split into groups depending on vehicle powertrain (BEV vs. PHEV), location of overnight parking (depot vs. home), and home charging availability for LCVs without depot.

As for 2 and 3 wheelers, the minimum group characteristics include powertrain, home charging availability, depot charging availability, commuting status, and workplace charging access for commuters.

The decision to require this minimum classification is based on EV drivers' survey and market research. These have shown that EV drivers charging behavior largely depends on the availability of home, depot, and workplace charging.

Table 2 below presents an example of how the basic user groups look like for passenger cars.

Table 2. Example of basic EV groups for private passenger cars

Group ID	EV driver group characteristics			
	Powertrain	Home charging access	EV used for commuting	Workplace charging access
1	BEV	Yes	Yes	Yes
2				No
3			No	NA
4		No	Yes	Yes
5				No
6			No	NA
7	PHEV	Yes	Yes	Yes
8				No
9			No	NA
10		No	Yes	Yes
11				No
12			No	NA

The model is designed so that users can include additional user group differentiation according to data availability and market characteristics. This is made possible through a flexible “Consumer type” variable. A set of consumer types can, for example, be “high-income and long-range vehicle”, “low-income and long-range vehicle”, “high-income and short-range vehicle”, and “low-income and short-range vehicle”. As another example, behavior groups could depend on the use type of LCV: delivery, trade vehicle for plumbers, carpenters, or other craftsmen, etc.

Splitting EVs into different behavior groups requires lots of data that is not always accessible. We thus often have to use proxies. For home charging availability, households' dwelling type is used as a proxy. EV owners living in houses are more likely to have access to home charging than those living in apartments. Similarly, EV owners renting their homes are less likely to have access to home charging than those owning their homes.

2.1.3 Calculating and splitting the energy required by charging setting

After this, in Step 3, the daily energy required is forecasted for each charging group based on annual electric mileage and vehicle efficiency (in kWh per mile). Vehicle efficiency takes into account technology improvements and changes in vehicle mass. This annual electricity demand (in kWh) is then allocated to different charging settings (a setting is defined by the location and type of charger, previously described). Table 3 below provides an example of how the total energy demand is allocated.

The split of energy demand by charging setting is based on charging behavior survey of EV drivers and regulations (for example, if a jurisdiction has incentives in favor of workplace

charging or if a certain jurisdiction offers free public destination AC charging, then the share of energy coming from these two settings could increase).

Table 3. Example of energy split by charging setting.

Public vs Private		Share of energy coming from									
		Private				Public					
Charger Location		Home	Workplace	Depot		Overnight	Destination		En-route		
Type		Level 1 or Level 2	Level 2	Wired stationary charging	Battery swapping	Level 2	Level 2	DC	Battery swapping	DC	Battery swapping
Group ID	1	a1%	b1%	c1%	d1%	e1%	f1%	g1%	h1%	i1%	j1%
	2	a2%	b2%	c2%	d2%	e2%	f2%	g2%	h2%	i2%	j2%
									

*a1% + b1% + c1% + d1% + e1% + f1%+g1% + h1% + i1% + j1% = 100%

2.1.3 a) Reallocating energy demand

While for home and public overnight AC chargers, the chargers are located where people live, i.e. where they register their car, this is not the case for workplace, public destination, and en-route chargers. Indeed, public destination chargers are usually located where people shop, take public transit, and do leisure activities. Similarly, workplace chargers are located where people work, and not where they live.

The user thus needs to input origin-destination matrices to reallocate workplace and public destination charging needs to the right locations. While commuting origin-destination data usually exist, it is harder to obtain origin-destination data for public destination charging. We thus often aggregate all the energy delivered through this type of charging at the analysis level and then split it among jurisdictions based on proxies. As example, the proxies used for public destination charging location can be the square footage of commercial centers or number of parking spaces.

As example if an analysis is composed of 3 jurisdictions (A, B, and C), the origin-destination matrix for workplace could look like Table 4 and the public destination energy demand reallocation could look like Table 5. The last row and column refer to the case when there are some vehicles that need to charge in jurisdictions in the analysis but come from out of the analysis. In that case, the user has to provide an additional “out of analysis vehicle” input file.

Table 4. Origin-Destination matrix example for workplace energy demand

		Origin (where the EV is registered)			
		A	B	C	out of analysis (number of vehicles)
Destination (where the EV is charged at the workplace)	A	50%	40%	20%	500
	B	20%	50%	5%	1,500
	C	20%	10%	70%	700
	out of analysis	10%	0%	5%	

Table 5. Redistribution of energy demand for public destination charging.

	Share of the total public destination energy distributed in each jurisdiction
A	60%
B	30%
C	10%

2.1.4 Calculating the total number of chargers needed

Step 4 translates this electricity demand (kWh) into the number of chargers required based on estimated charging efficiency, active utilization, and capacity.

Charger and on-board converter efficiencies

There are energy losses when charging an EV. The model accounts for two types of losses which vary depending on the charging type (mostly depending on whether the charger is an AC or a DC one). The first efficiency is the charger efficiency ($\frac{\text{electricity exiting the charger}}{\text{electricity entering the charger}}$) and the second one is the vehicle on-board efficiency ($\frac{\text{electricity entering the battery of the EV}}{\text{electricity exiting the charger}}$). These losses are mostly due to the AC-DC conversion.

Charger active utilization

For public and workplace chargers, we assume a logarithmic increase of active utilization (i.e. the share of time during which power is actively drawn from the charger or time during which the battery is swapped, so not including plugging and payment downtimes), as a function of electric vehicle stock share, until a maximum utilization is reached at mass EV adoption (see equation 1 below). The coefficient a and b are determined based on assumptions for minimum and maximum utilization for given EV stock shares (the utilization is flat before the minimum and after the maximum stock shares). As an example, the maximum utilization is, by default, set at 6 hours per day for public wired stationary chargers (i.e. 25% utilization) and 5 hours per working day for workplace chargers (i.e. 15% utilization) [3], but it can be modified by the user.

$$\text{Active charger utilization (in percentage of the time)} = a * \ln(\text{EV stock share}) + b \quad (1)$$

Capacity

The concept of capacity slightly differs for wired stationary charging and for battery swapping.

Wired stationary charging: Power delivery

The average power delivered by each charger type (AC overnight, AC and DC destination, and DC en-route) and capacity (e.g. 22kW and 50 kW) is estimated for every year of the analysis. The average power actively delivered during a charging session should not be mistaken for the rated power output of the charger and is usually limited by the vehicle. As example, a 50 kW charger might only deliver 45 kW on average during a charging session. This average power delivery mainly depends on the vehicle's charging acceptance rate, the start and end SOC of the vehicle, and the rated power output of the charger.

As default, we generally assume a slight increase in power delivery ratio $\left(\frac{\text{average power delivered during a session}}{\text{rated power output of the charger}}\right)$ over the years due to technological improvements and better understanding of vehicle capabilities from EV drivers. As an example, although in early years some BEV drivers might try and plug in at 100 kW DC chargers even if their BEV cannot accept more than 50 kW, this is less likely to happen in later years with a better understanding of the vehicles' limitations. Similarly, while in early years, some BEV drivers might try and charge their vehicle at a DC fast charger above 80% SOC, this is less likely to happen in later years.

Battery swapping: Station size

It is important to note that, most of the time, battery swapping stations are specific to a certain battery type and placement in the vehicle. The model thus assumes that battery swapping stations are specific to a vehicle and a segment. For example, a battery swapping station can be dedicated to 2-wheelers (Vehicle category) whose batteries have been manufactured by company A (segment category). A battery swapping station is further defined by its capacity, or size, in terms of total available battery stock per station per day.

Calculation summary

Wired stationary charging

From Table 3, we know the percentage of energy that has to be delivered through a given charger type for a given consumer group. To calculate the number of a given charger needed (e.g. public destination DC, 100 kW) for a given jurisdiction and year, the equation (2) below is then used. This equation is simplified for one behavior group. In reality, we sum the part in blue for all consumer groups relying on the charger at stake.

$$\frac{\text{Number of chargers of a certain location, type and capacity} = \# \text{ vehicles in the consumer group} * \frac{\text{number of miles}}{1 \text{ day}} * \text{vehicle efficiency} \left(\frac{\text{kWh}}{\text{mile}}\right) * (x\%: \text{share of energy coming from this charger category for the consumer group}) *}{\text{power delivery ratio} * \text{rated power output} * \frac{1}{\text{utilization share} * 24\text{hrs}}} \quad (2)$$

Battery swapping

From Table 3, we know the percentage of energy that has to be delivered through different locations of battery swapping stations in a given jurisdiction. As an example, if a user group gets 20% of its energy through swapping their battery, it means that 1 out of 5 times their energy is depleted, they go to a battery swapping station, while for the 4 other times, they will use conductive charging to recharge their EV. Alternatively, it can also mean that 1 out of 5 EVs in that group only use public destination battery swapping while the other 4 out of 5 EVs never use battery swapping. For the latter, we encourage users to define a battery-swapping-only additional “consumer type”.

To calculate the number of battery swapping stations needed (of a certain type and capacity) for a given jurisdiction and year, the equation below is then used. This equation is simplified for one behavior group. In reality, we sum the part in blue for all consumer groups relying on the battery swapping station at stake.

$$\text{Number of battery swapping stations (BSS)} = \# \text{ vehicles in the consumer group} *$$

$$\frac{1 \text{ battery}}{x \text{ kWh (battery capacity)} * (1 - \text{MinSOC})} * \frac{\text{number of miles}}{1 \text{ day}} * \text{vehicle efficiency} \left(\frac{\text{kWh}}{\text{mile}} \right) * (x\%: \text{share of energy coming from this BS type for the consumer group}) * \frac{1}{\text{BSS utilization}} \quad (3)$$

The following equation is used for battery swapping station utilization:

$$\text{BSS daily utilization} = \min \left(\frac{\# \text{available battery stock}}{1 \text{ station} / 1 \text{ day}}, \frac{\text{utilization share (\%)}}{\text{swap time (min)} * \frac{1}{24 * 60 \text{min}}} \right) \quad (4)$$

2.2 Minimum coverage

There are three sub-types of minimum coverage methodologies: vehicle-based, distance-based, and population-based.

2.2.1 Vehicle-based

This methodology is usually used for private home and depot chargers.

For private home chargers, the total number is directly correlated to the vehicle stock. For chargers in houses, by default there is one home charger per BEV with access to home charging and slightly less than one charger per PHEV with access to home charging, assuming that PHEVs sometime share chargers with another electric vehicle. For chargers in apartments, there is, by default, one home charger per 2 electric vehicles. The user can modify these default values.

For depot chargers, the user is asked to provide a ratio of kW of installed power output per BEV and per PHEV. By default there is 8kW of installed power output per BEV and 4kW per PHEV. The user then provides details on the type of chargers used by the fleet of vehicle using these depot chargers. For example, the fleet could source half of their energy from 11kW AC chargers and half from 50kW DC chargers at the depot.

This methodology could also be used to calculate the number of en-route chargers, even if this is not the default approach. Indeed, they could depend on the number of BEVs on the road instead of depending on the distance between two charging stations (see below) or the energy they need to provide.

2.2.2 Distance-based

This methodology is mostly used for fast chargers along road corridors (public DC en-route charging).

The number of DC en-route chargers is usually based on the length of the road network and requirements on the maximum distance between charging stations and the minimum number of chargers per charging station. Indeed, the number of corridor chargers needed depends less on the annual energy they need to deliver than on a basic coverage able to meet the vehicle throughput on high-activity days such as holidays and weekends. For example, if a road network in the jurisdiction is 1,000 km long and regulation mandates the need for charging stations every 100 km with a minimum of 4 chargers per station, then the jurisdiction at stake will need 40 public en-route chargers at 10 different stations. It is on the user to provide the roadway length per jurisdiction along with the number of charging stations every 100km.

2.2.3 Population-based

Certain jurisdictions may mandate a minimum number of chargers based on the number of inhabitants to ensure basic coverage and equitable charging access. Once this base minimum is reached, additional chargers can be deployed where there is demand, using the energy-based approach. This straightforward methodology could ensure minimum public overnight and destination charging coverage.

2.3 Potential additional steps

After obtaining the total number of chargers, there are two potential additional steps. They are shown in steps 5a) and 5b) in Figure 1 and are applicable regardless of which methodology is chosen to calculate the number of chargers (energy and minimum coverage).

2.3.1 Calculating total installed public power output per BEV and per PHEV

For the first additional step (5a.), the total public power output is estimated based on the number of chargers in each public charging setting (*location* and *type*) and assumptions related to the rated power output of these chargers (*capacity*) and then divided by the electric vehicle stock from Step 1.

2.3.2 Calculating investments needed

For the second additional step (5b.), the total cost of both public and private charging infrastructure is estimated based on charging infrastructure capital and operational costs estimates. For capital costs, there are 7 categories by default: hardware, software, planning, installation, grid connection, grid upgrade, and land acquisition. For operational costs, there are 3 categories by default: maintenance, grid upgrades, and land rental. Grid upgrades and cost of land are listed in both operational and upfront costs as they can be either depending on business arrangements: Sometimes utilities will offer charge point owners to spread grid upgrade cost over multiple years and sometimes charge point operators will purchase the land while in other cases they will rent it. The user can input additional capital and operational cost categories as needed, cost of permits could be an example.

3. Inputs and outputs of the model

3.1 Inputs fed to the model

A list of inputs has to be provided by the user to run the model. The inputs are split into three categories: *Default*, *User-provided mandatory*, and *User-provided optional*.

Default inputs refer to all the inputs that are provided by default when someone uses the model. The user is encouraged to modify some of these inputs to better fit the market analyzed. User-provided mandatory inputs refer to the inputs the user must provide to run the model. Without these basic inputs, the model cannot be run. Finally, user-provided optional refers to inputs that the user can additionally provide if such data is available for the market analyzed in order to have more granular results.

Table 6 provides a list of all the input files classified in the three aforementioned categories. The default and optional input files highlighted in light orange refer to input files that are not mandatory, but the results' accuracy is significantly enhanced if the user provides them to adapt to the specificities of the market analyzed. All the inputs can depend on vehicle (PC,

LCV, 2-wheeler, 3-wheeler), segment (e.g. taxi, company car, vehicle operated by company A), and jurisdiction. Some of the inputs are fixed for all the analysis, while others can potentially vary based on the year or the EV stock share. This information is provided in italic after the name of the input: $f(\text{years})$ or $f(\text{EV stock share})$.

Table 6: Inputs fed to the EV CHARGE model.

Default	User-provided mandatory	User-provided optional
EV per charger (e.g. EV per home charger in apartments and per home charger in houses), <i>f(EV stock share)</i>	EV fleet input data (sales or stock, VKT, efficiency), <i>f(year)</i>	Consumer type
kW per EV depot charger (mostly for LCVs and taxis), <i>f(EV stock share)</i>	Housing share of EV owners, <i>f(EV stock share)</i>	Charger density by distance, <i>f(year)</i>
Depot charging type, <i>f(EV stock share)</i>	Share of EVs used to commute, <i>f(EV stock share)</i>	Roadway length
Home charging access share for various dwelling types, <i>f(EV stock share)</i>	Depot charging access (mostly for LCVs and taxis), <i>f(EV stock share)</i>	Charger density by population, <i>f(year)</i>
Share of workplaces offering charging access, <i>f(EV stock share)</i>		Population
Commuter VKT ratio (ratio of VKT driven by commuters vs non-commuters)		Charger lifetime by installation year, <i>f(year)</i>
Charger upfront cost, <i>f(year)</i>		Current charger installed base
Charger operating cost, <i>f(year)</i>		Age distribution of existing chargers
Efficiencies (charger and on-board efficiencies), <i>f(year)</i>		Redistribution of workplace chargers
Charger power delivery ratio (average power delivered during a session vs. rated power output for each charging setting), <i>f(year)</i>		Redistribution of public destination chargers
Charger utilization, <i>f(EV stock share)</i>		Redistribution of depot chargers
Evolution of new charger installed share per rated power output, <i>f(year)</i>		Out-of-model vehicles, <i>f(year)</i>
Min SOC		
Battery swapping station characteristic		
User group definition (see Table 2 for an example)		
User group usage share (see Table 3 for an example)		

3.2 Outputs of the model

After feeding the inputs in EVCHARGE, selecting the desired methodology (or the mix of methodologies, max(energy, minimum coverage population) for example) for each charging setting, and running the model, the user obtains a csv file. The model outputs the total number of chargers of each setting needed for every vehicle type, jurisdiction, and year of the analysis.

Another csv file can be provided to the user for the breakdown of the cost per type (grid connection, land, hardware, software, etc.). The csv output structure with one or two row(s), as an example, is provided below.

Table 7: Example of csv outputs from EV CHARGE (main output, subdivided in 2 tables to fit in the page)

Variables	ISO	Subregion	Vehicle	Segment	CY	Charger location	Charger sublocation	Charger Type
Examples	USA	California	PC	Private	2025	Home	Apartment	Level 2
	DEU		PC and LCV		2030	En-route		DC

Power output of the charger	Roadway type	Total energy needed from the grid in CY (kWh)	Total installed power output in kW	Total number of chargers	Cost incurred in CY	Chargers installed in CY	Chargers removed in CY	Methodology chosen
		A1 kWh	A2 kW	X1	\$ xxx	X2	X3	Vehicle
150 kW	TEN-T core network	B1 kWh	B2 kW	Y1	\$ yyy	Y2	Y3	Distance

Table 8. Example of csv cost output from EV CHARGE (cost breakdown output)

Variables	ISO	Subregion	Vehicle	Segment	CY	Charger location	Charger sublocation	Charger Type	Number of chargers	Cost type	Cost value	Methodology chosen
Example	IND	New Delhi	3 wheeler	Company A	2030	Public desination		DC	X	Operating maintenance	\$ xxx	Energy

4 Case study for ZEVTC jurisdictions

The ICCT is currently developing this model, which should be ready by April 2023. In the meantime, the authors present a case study based on the same modeling framework to exemplify the usefulness and output types of this model.

This modeling methodology has been used to estimate public and private charging infrastructure needs up to 2035 for the 17 jurisdictions of the Zero-Emission Vehicle Transition Council (ZEVTC). [1][4] Several of the results are presented in the Figures below.

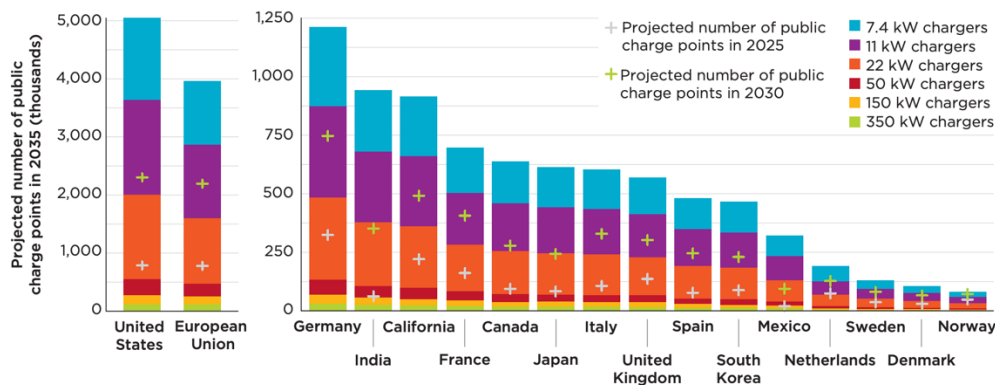


Figure 2. Number of public charge points needed for light-duty electric vehicles in 2025, 2030, and 2035, split per rated power output.

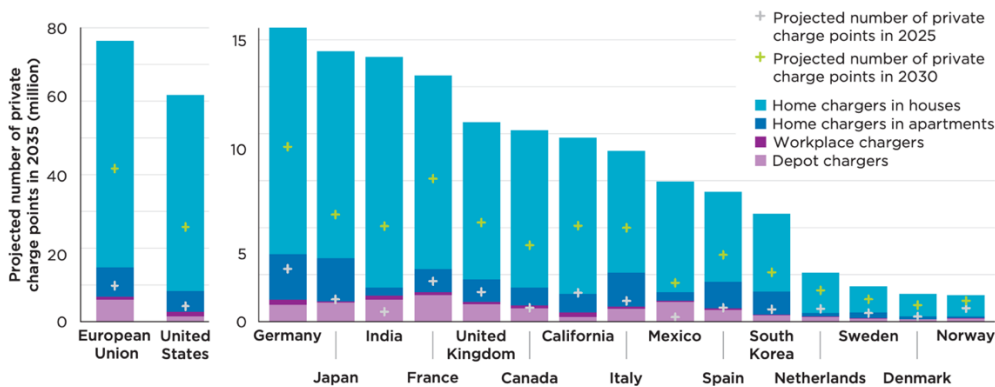


Figure 3. Number of private charge points needed for light-duty vehicles in 2025, 2030, and 2035.

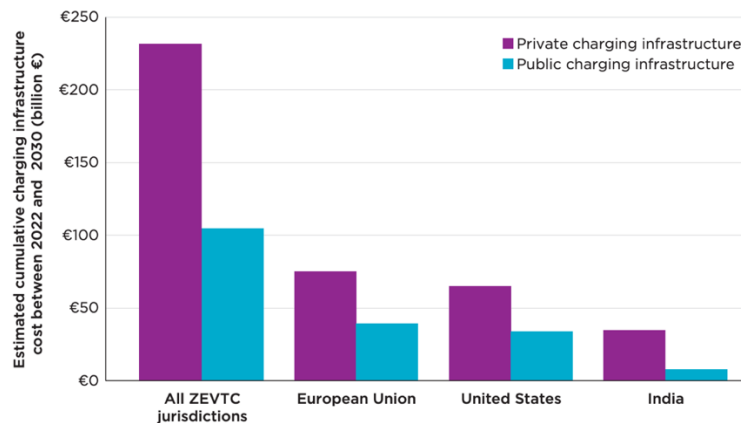


Figure 4. Order of magnitude of cumulative charging infrastructure cost between 2022 and 2030 for all ZEVTC jurisdictions, the European Union, the United States, and India.

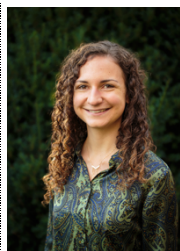
Acknowledgments

The development of this model was funded through the generous support of the Children’s Investment Fund Foundation, the European Climate Foundation, Climate Imperative, and the Heising-Simons Foundation. The authors would like to thank Dale Hall for his review of the paper and technical expertise provided during the development of the model, Gordon Bauer for his modeling ideas, and Tim Dallmann, Stephanie Searle, and Peter Mock for their logistics support.

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Presenter Biography



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