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TECHNICAL NOTE

SIMULATOR TO QUANTIFY AND MANAGE ELECTRIC VEHICLE LOAD IMPACTS ON LOW-VOLTAGE DISTRIBUTION GRIDS

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ABSTRACT

The Electric Vehicles on the Grid Simulator (https://ev-simulator.wri.org) is intended to help individual building energy managers, facility owners, distribution service operators, charging point operators, and fleet operators. This model-based simulator enables users to evaluate the potential electric vehicle (EV) load impacts on the low-voltage distribution grid at specific sites and plan for future capacity upgrades. Additionally, the tool can be used to quantify the effects of different vehicle-grid integration technologies to alleviate the peak capacity stress.

The Monte Carlo simulation and linear programming are deployed to predict the EV charging and discharging load profiles and load impacts at specific sites, with the consideration of future EV penetration, EV charging and traveling behaviors, availability of charging facility availability, and site loads. Based on existing studies conducted in the United States, Europe, and China, the default EV charging and traveling behaviors are predefined for a quick assessment. Users are encouraged to modify the model inputs for the specific site to derive more accurate and contextualized results. This tool can also help manage an EV fleet's smart charging and discharging at the low-voltage distribution grid.

CONTENTS

Technical notes document the research or analytical methodology underpinning a publication, interactive application, or tool.

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1. INTRODUCTION

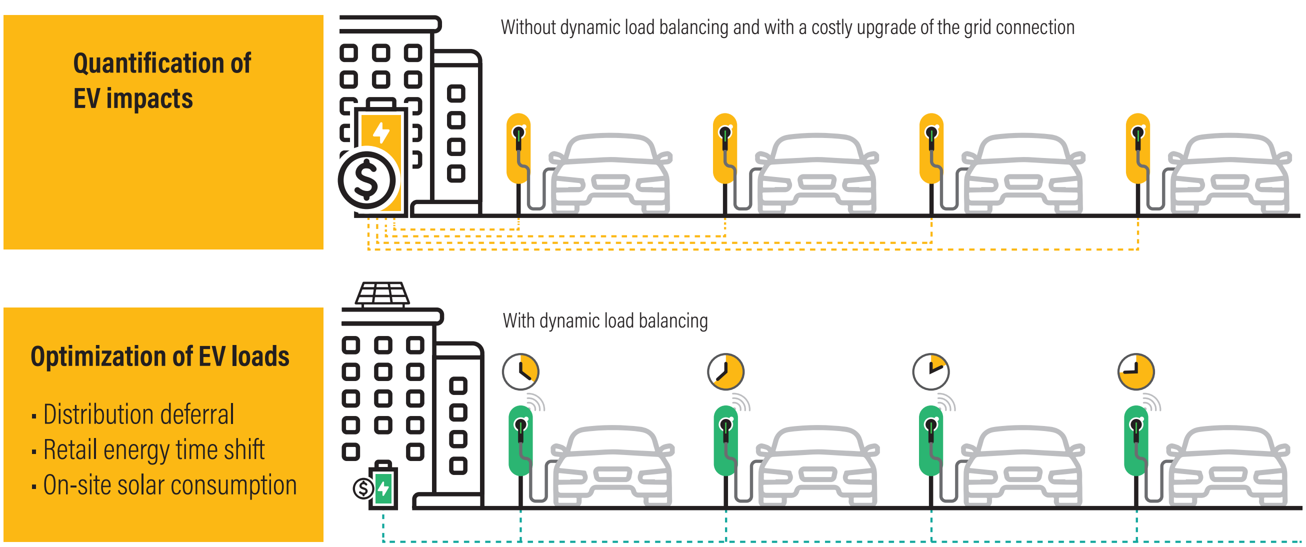
The increasing penetration of plug-in electric vehicles (EVs), including battery EVs and plug-in hybrid EVs, imposes a significant load on the low-voltage distribution grid, which consists of the low-voltage transformers and substations at a specific site. Accommodating the charging demands of EVs will involve expensive upgrades to local distribution systems. Nonetheless, vehicle-grid integration (VGI), as used in this study, enables EVs to provide grid services such as peak load shaving and to maintain an affordable and reliable distribution grid. To achieve this goal, EVs must have capabilities to manage charging or support two-way interaction between vehicles and the grid, which are referred to as "managed charging" and "vehicle-to-grid" (V2G).

The Electric Vehicles on the Grid Simulator (https://ev-simulator.wri.org) is a model-based simulator that provides two main functions, as shown in Figure 1:

- It helps individual building energy managers, facility owners,[1] distribution service operators, charging point operators, and fleet operators quantify the future EV load impacts on transformers or substations[2] at a specific site—for example, a residential neighborhood or an office building. It will also inform future low-voltage network upgrades, ensuring that EV load impacts do not exceed the current capacities of transformers and substations.
- It helps individual building energy managers, facility owners, distribution service operators, and charging point operators manage and optimize individual EV charging and discharging profiles through VGI measures to delay or possibly avoid expensive network upgrades (known as "distribution deferral"), reduce overall costs for electricity (known as "retail energy time shift"[3]), or consume on-site solar by leveraging EVs as a behind-the-meter energy storage system. In this case, the optimized EV charging and discharging profiles generated from the tool can be sent to charging points to directly manage the charging (or discharging) time and power of each EV.

The tool is not capable of modeling stationary storages or demand flexibility in buildings.

Figure 1 | **Purposes of the Simulator**



Notes: EV = electric vehicle. Yellow chargers are unmanaged chargers that will probably incur large investments in distribution grid upgrades. Green chargers are managed chargers capable of retiming the charging sessions to off-peak hours, thereby reducing the investment in distribution upgrades and also enhancing on-site solar consumption.

Source: WRI China authors.

2. MOTIVATION

The simulator was developed to assist utility companies and businesses to determine at what threshold EV adoption rates will overload the existing capacity of a transformer, a substation, or multiple substations in an area. Conventional methods of forecasting the peak loads of non-EV customers (such as commercial or industrial peak loads) on a transformer (or substation) are not suitable due to the variety of EV charging profiles. These conventional practices primarily include load surveys and the diversity factor method.

- Site load surveys rely on using the load profiles of similar facilities plus extra capacity allowances to project peak demands—an approach that is useful to forecast the demand of large users such as industrial or commercial customers (Munasinghe 1990).
- The diversity factor method builds on the fact that the maximum demands of individual customers or electrical appliances will not occur at the same time; thus, this demand is diversified (Bayliss and Hardy 2007; Smith and Parmenter 2016). The diverse nature of load demands motivates the use of the diversity factor—the reciprocal of the coincidence factor—and is important to utility companies in planning distribution grid expansion. Utility companies use empirical evidence to determine the diversity factors (or coincidence factors) for different types and sizes of customers. These companies then estimate peak load by applying this predefined diversity factor to discount the sum of individual maximum demands (Equation 1).

Equation 1

$$\text{Max load} = \frac{\sum_i \textit{max individual demand}_i}{\textit{Diversity factor}}$$

$$= \sum_i \text{max } \textit{individual demand}_i \times \textit{coincidence factor}$$

Because EVs present a new type of custom load that has no historic records, and the current number of EVs has not yet reached a critical mass for utility companies to capture its load characteristics or diversity factors, the above two approaches encounter limitations.

The simulator adopts an end user approach to forecast the future EV daily load that accounts for the randomness of EV charging and traveling behaviors. In the model, EV charging and traveling behaviors should be defined by the user based on the best available data. Defaults in this tool are based on existing studies carried out in the United States, Europe, and China (Stephens et al. 2012; INL 2015; Sadeghianpourhamami et al. 2017; California Energy Commission 2018; Gnann et al. 2018; and Xue et al. 2020). However, whenever the data are available, the user should make location-specific updates to these behavioral inputs to derive more accurate and contextualized results. The defaults only apply to the circumstances where the user has no data but is in need of a quick, rough assessment or where the user wants to understand the data needed to forecast potential EV load impacts and strives to set up a data collection system.

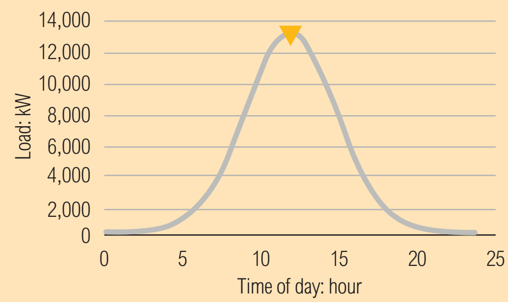
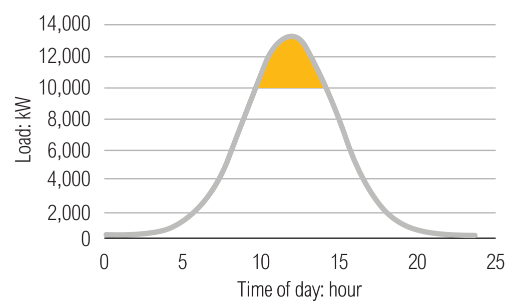
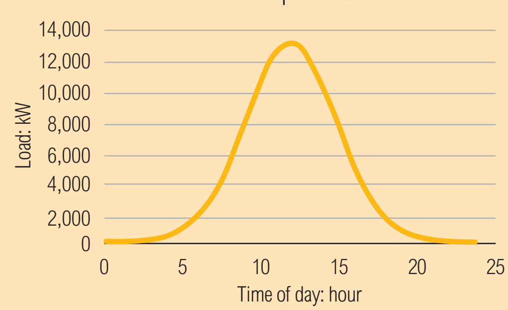
Whereas the Vehicle-to-Grid Simulator (V2G-Sim) developed by the Lawrence Berkeley National Laboratory[4] evaluates EV grid impacts at various levels, from distribution to transmission and wholesale market, the Electric Vehicles on the Grid Simulator focuses on EV grid impacts on the distribution level. Overall, this tool is a simplified version of V2G-Sim. With predefined use cases such as residential, office, and public, it is comprehensible to beginners and is therefore accessible for developing countries that are not familiar with the idea of VGI.

3. MODEL SCOPE AND APPLICABILITY

In the simulator, the grid impact is confined to the load demand impacts that are critical for distribution infrastructure planning and operational decisions (Table 1). Although EV charging also causes energy losses, voltage drops, and harmonic imbalance, these impacts can be mitigated with existing distribution grid equipment. Therefore, the simulator will focus only on the load demand impacts.

Different user groups with various concerns may focus on different aspects of the load curves. For example, utility companies are interested in peak demand when determining the capacity of the equipment needed to meet the customer's power requirements. They are interested in the near-peak load when setting utility tariffs to shift the load demands to off-peak hours. This simulator focuses on the entire load curve; therefore, it enables a whole spectrum of applications (Table 1).

Table 1 | **Load Curve Focus by User Group**

Entity	Applications	Focus
Distribution system operators (DSOs), facility owners	• Determine the capacity of distribution grid, as a result of increased electric vehicle (EV) penetration • Lower the expenses on demand charges[a] for facility owners	Peak load 
Regulators, utility companies	• Understand charging behavior over a time period to determine utility tariff	Near-peak load 
Charging point operators, DSOs, facility owners, customers	• Optimize EV load impacts to maintain an affordable and reliable electricity system and to support on-site solar integration • Reduce cost for electricity for customers	Entire load profiles 

Notes: [a] A regular utility tariff is imposed on energy consumption (measured in kilowatt-hours) whereas a demand charge is imposed on peak power demand (measured in kilowatts; and sometimes energy consumption is combined) to reduce the stress on the generation, transmission, and distribution capacities. Demand charges are often applied to commercial and industrial users, which often have high peak power demands.

Source: WRI China authors.

EV load is the energy consumed by EVs throughout a day. Although load profiles can be characterized at different temporal resolutions and spatial scopes, the simulator deals with the following aspects:

- **Time resolution.** The simulator adopts the daily load at a one-hour interval because this interval helps to reduce the computational complexity for managed charging and V2G. However, compared with 15-minute or 30-minute intervals, a one-hour interval also loses the time granularity and accuracy needed in some applications, including the estimation of demand charge reduction (usually demand charges are metered at 15-minute intervals).

- **Spatial resolution.** The simulator is set on the transformer (ratings are available from 200 to 1,500 kilovolt-amperes) and the substation level (a set of transformers). Therefore, the simulator is able to examine the impacts from increased EV deployment on an individual transformer or substation at a specific site, such as a residential neighborhood or an office complex.

- **Time horizon of projection.** Although the simulator is able to evaluate the current status of EV load impacts, it is also capable of projecting medium-term or long-term load demand as a result of increases in EVs or improved vehicle performance. The medium or long term is usually more than three years, which corresponds to the lead time required for major distribution upgrades.

Transformers (or substations) at different locations, such as industries, offices, and residential neighborhoods, serve different customer groups. Each customer group has unique demands and load curves. For example, in residential neighborhoods, energy consumption often occurs in the evening, whereas in offices most of the energy consumption occurs during the day. The simulator provides three predefined use cases that are common for EVs:

- **Residential Use Case.** Home charging is the most common charging location. In the United States, EV users perform 84 percent of charging at home (INL 2015); in China, EV users perform nearly 40 percent of charging at home (CATARC 2018).

- **Office Use Case.** Workplace charging either complements home charging—providing range extension to daily commuting (or long-range travel)—or substitutes for home charging. In the simulator, office charging is treated as a substitute for home charging rather than for range extension. Doing so could lead to an overestimation of EV grid impacts in the Office Use Case.

- **Public Use Case.** Compared to private home chargers and workplace chargers, public chargers are least used. At different venues, parking time and charging behaviors also differ. For example, at airport parking lots, EVs park for longer periods of time, whereas at direct current (DC) fast charging stations, EVs simply charge and go. The simulator takes the latter case as the default, but users can adapt the inputs to their needs.

Besides these three use cases, the simulator also allows for user-defined cases and for operating fleets such as electric freight vehicles. If the studied area is large and covers mixed uses, users can split customer segments and run the use cases separately.

4. MODEL DESCRIPTION

4.1 Model Structure

The simulator consists of three modules corresponding to the three ways that an EV can interact with the grid—namely, unmanaged charging, managed charging, and V2G (Figure 2).

Unmanaged charging module. This module evaluates the EV load impacts from the most common charging method, unmanaged charging, in which EVs are charged at full power rates as soon as they plug in until the batteries are full or the vehicles have to leave.

Managed charging module. Managed charging relies on a time-of-use (TOU) tariff or remote automatic control to shift EV charging loads to off-peak hours or align with renewable energy generation curves. The tool only models managed charging through remote automatic control by charging point operators or distribution service operators. Although TOU tariffs will incentivize EV drivers to charge at off-peak hours, how EV drivers will respond to peak-hour tariffs is an intricate research topic that is beyond this model. However, the simulator can model the optimized charging load through the combined approaches of remote control and TOU tariffs. For example, the simulator can derive optimal charging profiles that minimize the drivers' utility costs through automatic control.

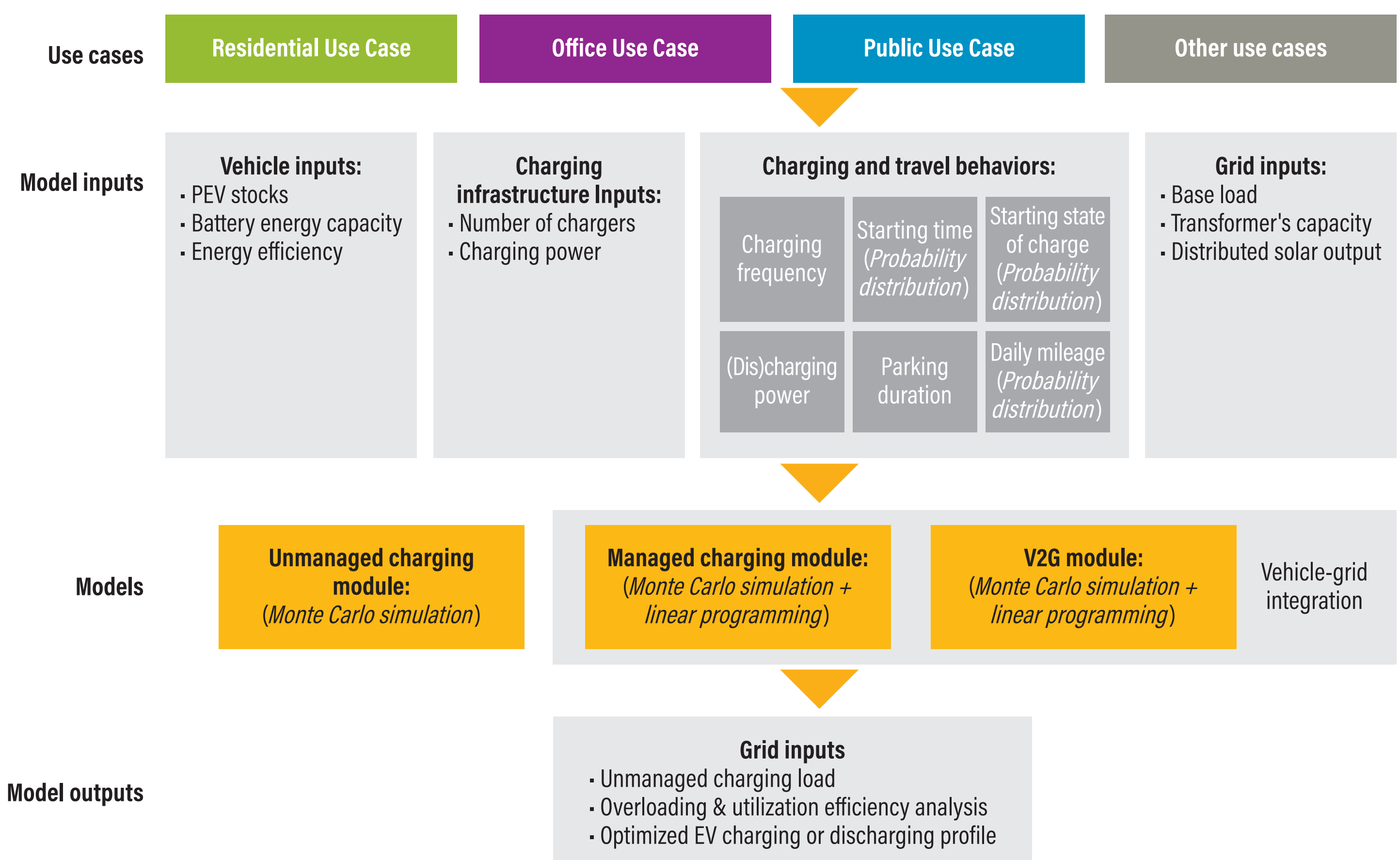
V2G module. V2G allows for bidirectional power flows between the vehicle and the grid. The V2G module simulates how V2G optimizes EV charging or discharging load profiles without compromising the vehicles' travel demands or fully depleting the batteries.[5]

It is worth mentioning that managed charging and V2G technologies by nature have limited applicability—this has nothing to do with the tool:

- VGI technologies may not work well for Level 1 chargers (charging power rate between about 1.4 and 3.4 kilowatts) because they are slow and require many hours to charge fully, usually leaving little time flexibility for VGI.
- VGI technologies also may not work well for short parking times in the Public Use Case because the short dwell time does not allow for vehicle-grid interactions.

The three modules are realized in both an online web application and an offline Python script. The unmanaged charging module and managed charging module are available both online (in the web application) and offline (in the Python script), whereas the V2G module, which requires a longer running time, is available only in the Python script. Furthermore, the online web application allows for simplified model inputs for easy maneuvers, whereas the Python script provides adaptation options to the model inputs and the functions. The differences between the web application and the Python script are summarized in Section 5.1.

Figure 2 | **Model Structure**



Notes: EV = electric vehicle; PEV = plug-in electric vehicle; V2G = vehicle-to-grid.

Source: WRI China authors.

4.2 Model Inputs

The simulator evaluates EV load impacts based on two types of load profiles: base load (non-EV load) and EV load. If distributed solar photovoltaic systems are installed on site, the solar output curve can also be included in the simulator to offset the EV load or base load.

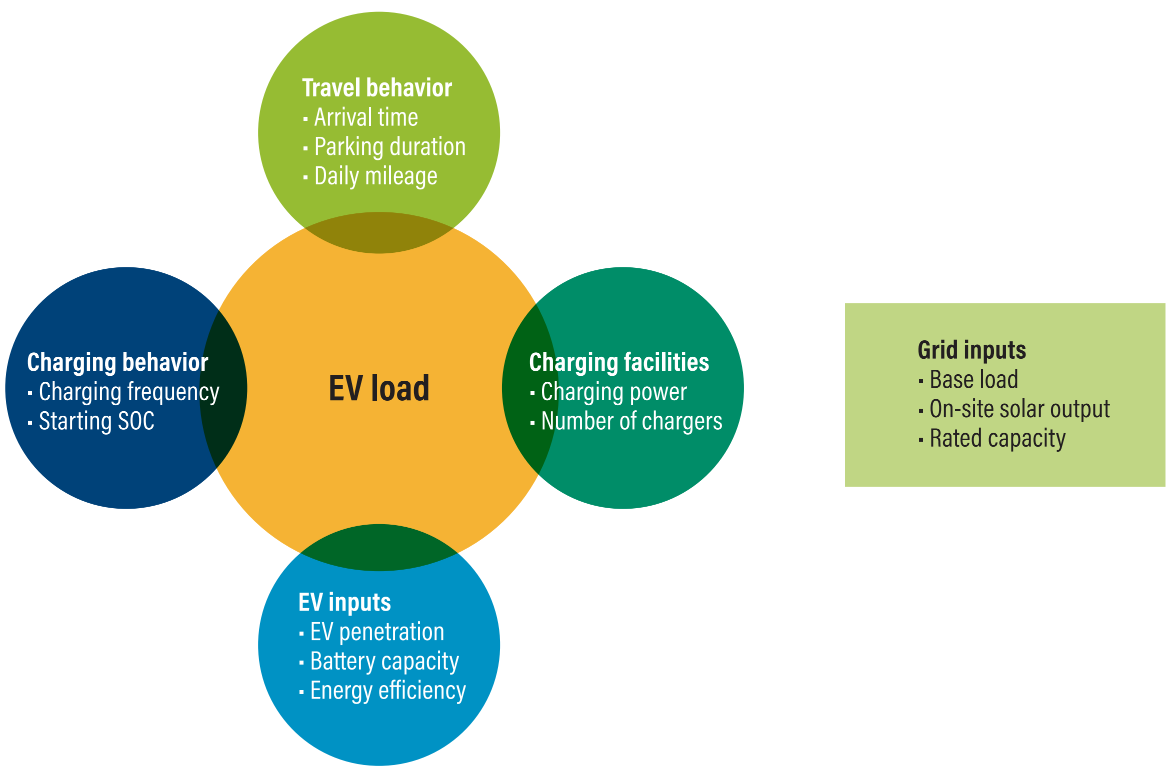
The base load is taken as the daily load curve of a typical day collected from local meters or predicted using the methods outlined in Section 2. Since the tool only focuses on EV loads, the prediction of the base load is beyond the scope of the tool.

EV load curves are model results that use the following information as inputs (Figures 3 and 4):

- EV inputs, including EV penetration rates, and technical performances such as battery energy capacity and energy efficiency.[6] A site may have multiple EV brands and models characterized by different technical performances. To reduce the model input workload, the online application only asks users to put in a typical and prevailing vehicle model. The Python script can be tweaked to allow users to specify multiple vehicle models and their numbers and technical performances.
- Charging facility inputs, including the number and types of chargers, and charging power ratings.
- Travel patterns, such as arrival time and departure time (that is, parking duration), to the parking lot.
- Charging patterns, such as the starting state of charge (SOC), and charging frequency.

To account for the stochastic nature of these travel and charging behaviors, behavioral inputs, such as travel

Figure 3 | **Model Inputs**



Notes: EV = electric vehicle; SOC = state of charge.

Source: WRI China authors.

Figure 4 | **Model Inputs for the Online Tool**

Grid inputs

ENTER BASE LOAD

☐ Include on-site solar power?

Rated capacity
4000 kVa

ENTER SOLAR CURVE

Vehicle inputs

Vehicle's battery capacity
50 kWh

Vehicle's energy efficiency
13 kWh/100 km

Number of electric vehicles
400

Fast charging vehicles (%)
100

Charging facility inputs

Number of fast chargers
400

Fast charging power
10 kW

Number of slow chargers
100

Slow charging power
7 kW

Travel and charging behaviors

Charging frequency ⓘ
5 Days/Charge

Arrival time ⓘ
08:00 PM

Time range of arrival time ⓘ
2 Hours

Average starting SOC ⓘ
60 %

Potential range of starting SOC ⓘ
20 %

☐ Enable managed charging?

Vehicles participating in managed charging (%)
10

Parking duration
8 Hours

Notes: kVa = kilovolt-ampere; SOC = state of charge.

Source: WRI China authors.

and charging patterns, are expressed in randomly distributed variables.

EV charging loads are generally computed based on charging starting time (the time when a charging session starts), the duration of the charging session, and the average charging power used throughout the charging session. The ways to specify or derive these three variables differ between the unmanaged charging module and the two VGI modules (Table 2).

Charging starting time. The arrival time model input, collected from travel surveys or charging station observations, is a key input to derive the charging starting time (Figure 4). The arrival time of the EV fleet to the site is described in probability distributions to enable the Monte Carlo simulation. Arrival times in different use cases are characterized by different probability distributions (Figure 5). Users can make site-specific adaptations: the web application only allows users to define arrival time in the normal distribution by varying the means and the deviations or discrete distribution by specifying the number of EVs arriving at the site at each hour; the Python script allows for any type of distribution (continuous distribution, such as beta, and discrete distribution).

Besides arrival time, the calculation of charging starting time also depends on the charging strategies deployed:

- For unmanaged charging, the charging starting time is calculated by inferring the waiting time for charge points to become available, based on each vehicle's arrival time, the number of vehicles, and the number of chargers installed. For example, the fewer the chargers installed on-site, the longer the queue of vehicles that will be formed. Hence, the charging starting time will be delayed to a later time.
- For managed charging and V2G, the charging starting time is defined as the time when the charger is plugged in (but the charging or discharging session is not necessarily started); for simplicity, the model assumes the arrival time is a proxy of the charging starting time for EVs.

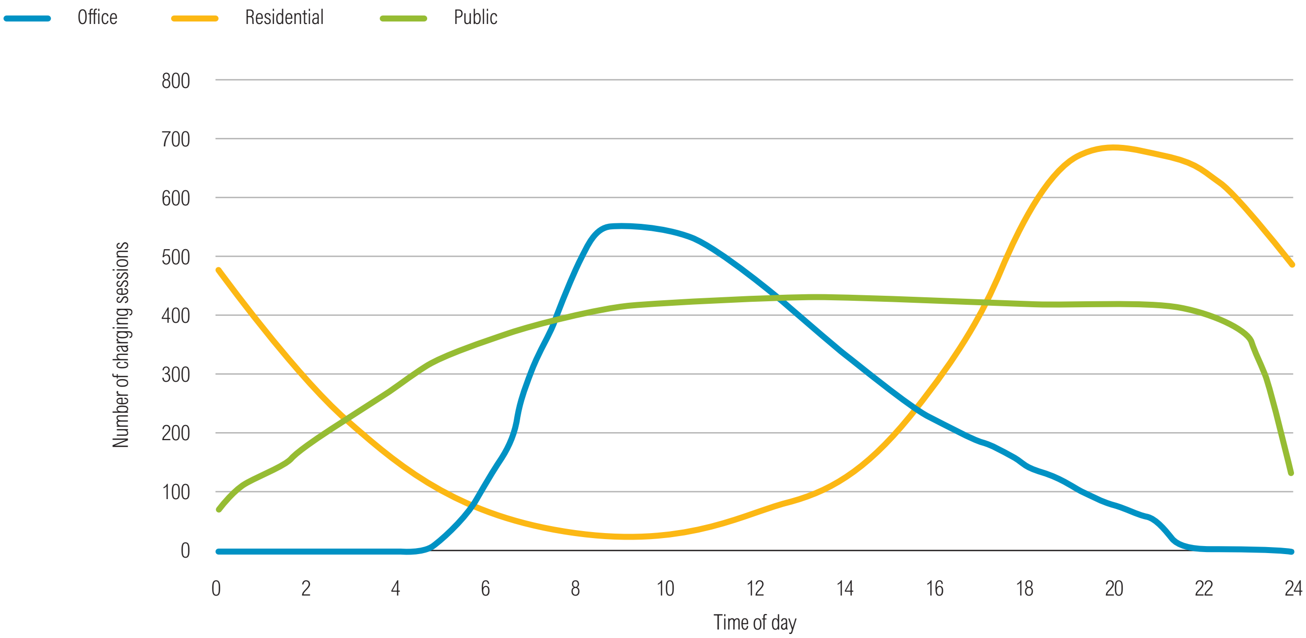
Table 2 | **Charging Starting Time, Charging Duration, and Charging Power Specifications**

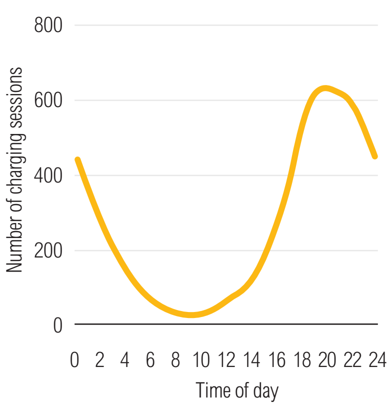
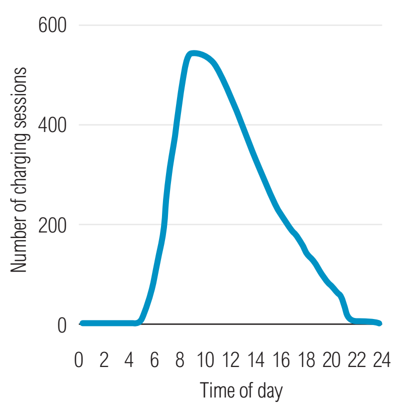
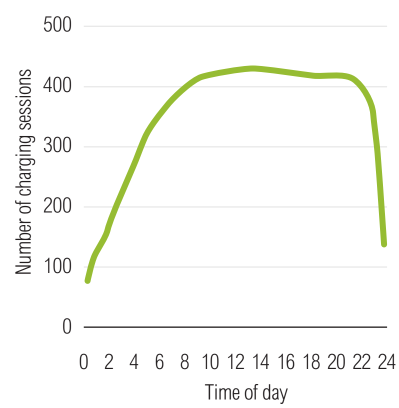
	Unmanaged Charging Module	Managed Charging Module, V2G Module
Charging starting time	Intermediary result derived from the arrival time and number of chargers available	Model input: arrival time
Charging duration	Intermediary result derived from starting state of charge (that can be further broken down to daily mileage, charging frequency, and battery range)	Model input: parking duration
Charging power	Model input: charging power	Model input: upper limit of charging (or discharging) power Model input: lower limit of charging (or discharging) power

Note: V2G = vehicle-to-grid.

Source: WRI China authors.

Figure 5 | **Examples of Arrival Time Distribution for the Three Use Cases**



Use Case	Residential	Office	Public and User-Defined
Model default	Normal distribution (mean 20:00, deviation 2 hours) 	Lognormal distribution (mean 9:00) 	Predetermined discrete distribution 
Web application	Normal distribution	Normal distribution	Normal distribution or discrete distribution

Notes: Based on existing studies—including Stephens et al. (2012), Sadeghianpourhamami et al. (2017), California Energy Commission (2018), Gnann et al. (2018), and Xue et al. (2020)—arrival times at homes, offices, and public venues in the United States, the Netherlands, and China exhibit regularities on weekdays due to similar commuting schedules. For example, arrival time shows a likely normal distribution pattern in residential neighborhoods, with a mean value around 17:00–20:00 and a possible lognormal distribution at workplaces with a mean value around 07:00–10:00. However, this model input can be tailored to the prevalent travel schedule of the specific site. Further, the y values are normalized so that the maximum y values across use cases are comparable in the same chart.

Source: The authors summarized data from the California Energy Commission (2018) and Gnann et al. (2018).

Charging duration. Charging duration is a key intermediary model result to produce EV charging and discharging profiles. It is derived from model inputs such as starting SOC or parking duration.

For unmanaged charging, the estimation of charging duration follows Equation 2—that is, the energy request divided by the charging power.[7] Since the starting SOC is a key indicator of the energy requested for each charging session, it is an important input to derive the charging duration.

Equation 2

$$T_i = \frac{E}{(P_c \times \varphi)} = (100\% - StartSOC_i\,) \times C/(P_c \times \varphi)$$

T_i is EV i's charging duration (i indicates the i-th EV on the site)
E is the energy request for one charging session (kilowatt-hours [kWh])
C is the energy capacity of batteries (kWh)
P_c is charging power (kW)
φ is charging efficiency (counting in energy loss during charging, fixed at 90 percent)

Because decisions on the amount of energy left in vehicles when charging (the charging starting SOC) vary greatly across use cases and have uncertainties in the future, the model provides three ways to estimate starting SOC:

1. **Daily mileage estimation.** When Level 1 slow charging is used in the Residential Use Case, private vehicles tend to be charged on a daily basis. As a result, starting SOC is determined by daily mileage traveled (see Equation 3 and Box 1).

Equation 3

$$StartingSOC_i = 100\% - \frac{d_i}{R}$$

d_i is EV i's daily mileage (kilometers [km])
R is the battery range (km)

2. **Multiple-day estimation.** As fast chargers become prevalent and battery ranges increase, EV drivers will opt to charge their cars less frequently (more than one-day intervals; Amsterdam Roundtable Foundation and McKinsey 2014; Charilaos et al. 2017; Van den Hoed et al. 2019; Vermeulen et al. 2019). In this case, charging starting SOC can be estimated by multiplying daily mileage by charging frequency—the number of days traveled since the last charge (see Equation 4)—to derive the energy demand. The value of charging frequencies can be obtained by surveys or a vehicle's onboard diagnostic (OBD) system (Table 3).

Equation 4

$$StartingSOC_i = 100\% - \frac{F \times d_i}{R}$$

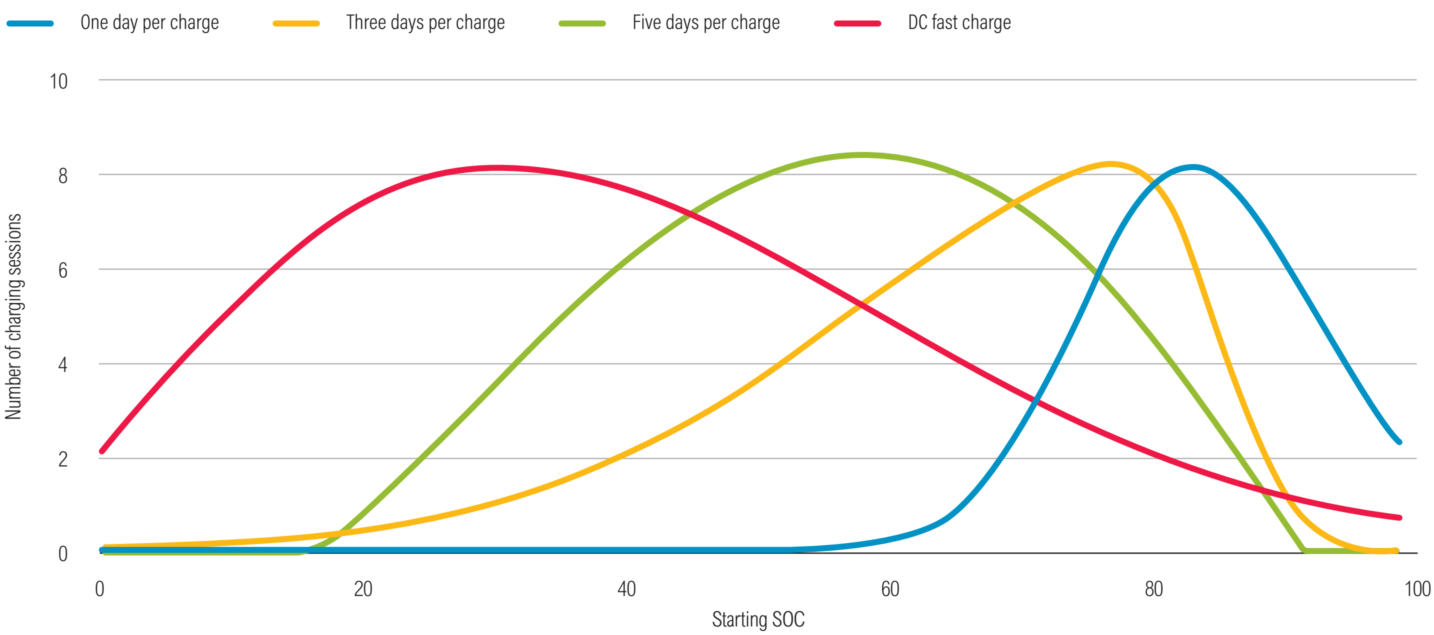
d_i is EV i's daily mileage (km)
F is charging frequency (the number of days since last charge)
R is the battery range (km)

3. **DC fast charging estimation.** When DC fast chargers or ultra-fast chargers in public charging stations are used, the vehicle's SOC is likely to be dropped to a low level, compared with the previous two cases. The model default input uses a beta distribution with the mean SOC value setting at 20 percent. Xue et al. (2020) examined the charging sessions of 70,375 private EVs in Beijing that use DC fast chargers based on OBD data and discovered that the distribution of the SOC fit a beta distribution with a mean of 20 percent. Empirical surveys of the charging habits of 8,300 EVs in the United States also show that the starting SOC for DC fast chargers peak around 20–30 percent (INL 2015).

Figure 6 shows the probability distributions of starting SOC using different estimation approaches. Significant variations exist: using 30 km as the average daily mileage (see Box 1), starting SOC is around 70–90 percent for one to three days per charge and 45–65 percent for five days per charge, and a mean of 20–30 percent is found for DC fast charging. As a rule of thumb, the daily mileage estimation and multiday estimation approaches are common for the Residential and Office Use Cases; the DC fast charging estimation is best applied to the Public Use Case in which DC fast chargers are used (INL 2015; Morrissey et al. 2016; Xue et al. 2020).

However, besides the three starting SOC estimation methods, the model also allows users to directly specify any possible distribution for charging starting SOC through surveys or OBD data analysis (Table 4).

Figure 6 | **The Probability Distributions of Starting SOC Using Different Approaches**



Use Case	Residential	Office	Public
SOC estimation method	• Daily mileage estimation • Multiday estimation	• Daily mileage estimation • Multiday estimation	• DC fast charging estimation • Multiday estimation

Notes: DC = direct current; SOC = state of charge.

Source: WRI China authors.

For managed charging and V2G, the charging duration is defined the same as the parking duration (that is, a model input). This provides enough time flexibility for managed charging or V2G control, but VGI may not work well for short parking durations. Since the EV's arrival time is a model input, parking duration is a proxy of the EV's departure time. If an EV is timed to leave early, it will have a shorter parking duration than other EVs. In the web application, to reduce the model input burdens for users, a constant parking duration for all EVs is applied, but users can tailor each EV's parking duration in the Python script.

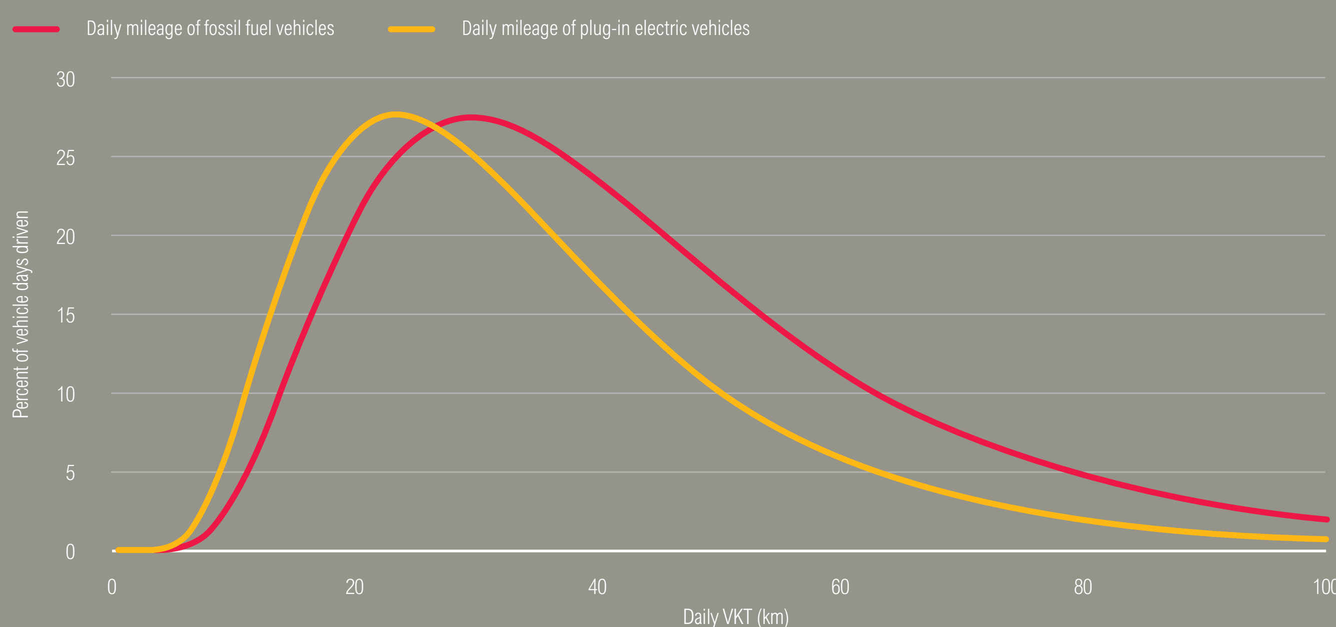
Box 1 | Electric Vehicle Kilometers Traveled per Year

Because of factors such as battery range, charging facilities shortages, range anxiety, and the self-selection of those choosing to use electric vehicles (EVs), the EV kilometers traveled (eVKT) per year is lower than the annual VKT of internal combustion engine (ICE) vehicles (Speidel and Bräunl 2014). According to the Idaho National Laboratory (2015), the annual average eVKT in the United States was around 15,366–15,606 kilometers (km; a daily distance of approximately 42 km), whereas the annual VKT for ICE vehicles was 18,259 km (a daily distance of approximately 50 km).

Besides distinctions between vehicle technologies, annual VKT also varies by country and city. Because of the differences in built environment, vehicle ownership, and travel demand management requirements, China's annual VKT for ICE vehicles averaged around 13,000–13,500 km in 2016 (a daily distance of around 35 km) (Ou 2019), lower than the U.S. average of 18,259 km (a daily distance of around 50 km). Based on the onboard diagnostic analysis of 230,000 private EVs in selected Chinese cities in 2018 (Xue et al. 2020), the annual eVKT is around 10,950 km (a daily distance of approximately 30 km).

As manufacturers continue to increase battery ranges, the daily mileage of EVs is also expected to increase, becoming comparable to that of ICE vehicles. The simulator uses the VKT distribution of ICE vehicles in China as the default eVKT. However, users can tweak the deviation of the VKT distribution to the specific context in the Python script.

Figure B1.1 | A Comparison of eVKT and VKT in China



Notes: For a city, region, or country, the vehicle kilometers traveled (VKT) and electric vehicle kilometers traveled (eVKT) of all private cars follow a lognormal distribution with different means and deviations (Plotz et al. 2014). In the above chart, eVKT distribution is lognormal (μ=3.44,σ=0.532) and VKT distribution is lognormal (μ=3.67,σ=0.532).

Source: WRI China authors.

Charging power. Charging power rates are differentiated between user-specified charging power rates (in the case of unmanaged charging) and controlled charging power rates (managed charging or V2G).

For unmanaged charging, charging power is the power rate of the charging facilities. Different use cases have different types of charging facilities (see Table 3). For some use cases, such as the residential setting, where multiple types of chargers are available (Level 1 and Level 2), the tool allows users to specify up to two types of chargers and the number of EVs that use each type of charger.

For managed charging or V2G, (dis)charging power is controlled by a second party, such as a charging point operator or distribution system operator, and the power rates are assigned dynamically to vehicles, depending on the load demand and the capacity of the transformer (or substation); model users only need to specify the upper and lower limits of the (dis)charging power allowed by the vehicle (Table 3). For example, a Nissan Leaf can only take the lower limit of 1.3–1.5 kW; otherwise, it will be locked out and disconnected from the charging.

All of the model inputs can be tailored by users to reflect the situation at the specific location. Tailored model inputs for current travel and charging behaviors can be obtained in three ways (Table 4):

- **Charging point operators** can provide detailed charging session information for sites. Such data often include EV arrival times and charging powers. However, each EV's charging frequencies, starting SOC, daily mileage, and parking duration are not traceable from this approach.
- **OBD data,** which monitor battery performance almost in real time, can provide insights into charging starting SOC and daily mileage from sampled vehicles or all the vehicles visiting the site. Upon agreement with the EV owner, the OBD data are transported via the vehicle's telematic systems.
- **Community-level travel surveys** conducted by model users or site owners can sample EV owners or all EV owners visiting a site. Typical surveys include, but are not limited to, questions about how often the owner charges the car at the site; the typical SOC when starting a charging session; the average daily mileage; and how long, on average, the car is parked at the site.

Table 3 | **Types of Chargers Used in Different Modules and Use Cases**

	Residential	Office	Public
Unmanaged charging module:			
Types of chargers and power ranges	• Level 1 • Level 2	• Level 2	• Level 2 and direct current (DC) fast charging
Vehicle-grid integration modules:			
Types of chargers and power ranges	• Level 2	• Level 2	• Level 2 and DC fast charging
Lower limit of charging power	The lower charging power limits allowed by electric vehicles		

Notes: Level 1: 1.4–3.4 kW; Level 2: 3.4–19.2 kW; DC fast charging >20 kW.

Source: WRI China authors.

Table 4 | **Comparison of Three Collection Methods for Model Inputs**

	Data Collection from Charging Point Operators	Vehicle OBD and Telematic System	Community-Level Travel Survey
Arrival time	√	√	√
Charging starting SOC		√	√
Charging frequencies		√	√
Daily mileage		√	√
Charging power	√	√	√
Parking duration		√	√

Notes: OBD = onboard diagnostic; SOC = state of charge. "√" indicates the input is available through the indicated approach.

Source: WRI China authors.

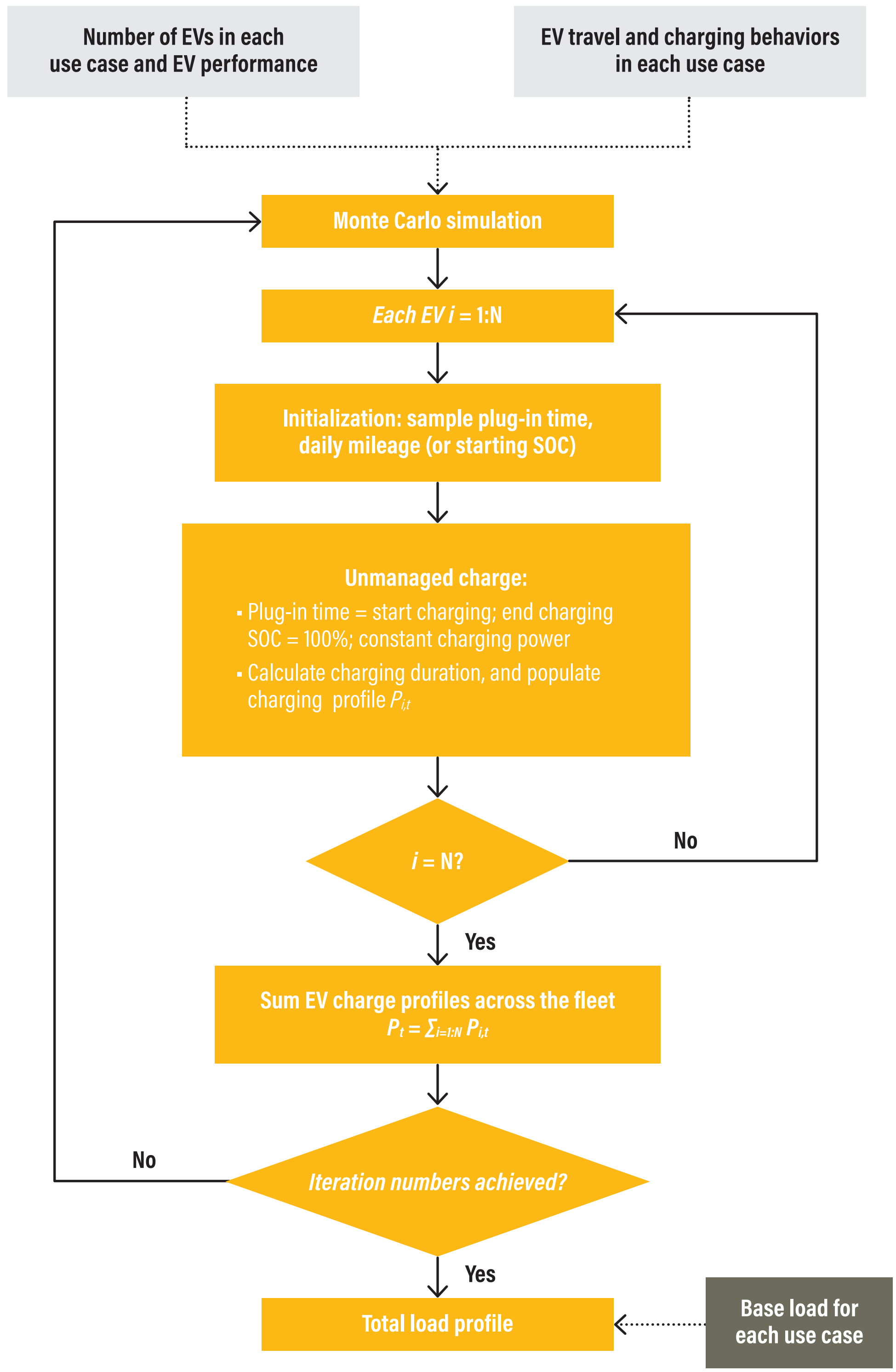
The model inputs can be predictive, such as when users conduct a scenario analysis to project the future load impacts of EV charging on the distribution grid. Predictions require assumptions about charging behaviors—whether they will remain the same or change in the future. For example, at present, in the residential setting, EV owners tend to charge the vehicles on a daily basis. But this behavioral pattern could evolve into multiple days between charges as battery ranges increase over time (Amsterdam Roundtable Foundation and McKinsey 2014; Charilaos et al. 2017; Van den Hoed et al. 2019; Vermeulen et al. 2019). Because the evolution of future charging behavior is uncertain, users can run the model multiple times, each time with different inputs, to assess the EV load impacts of different charging behaviors.

4.3 Model Methodology

4.3.1 The Unmanaged Charging Module

The unmanaged charging module employs the Monte Carlo simulation to evaluate the grid impacts of unmanaged charging. The Monte Carlo simulation is used to initiate the beginning state of each EV, including arrival time, charging starting SOC, and daily mileage, by randomly drawing values from the probability distributions. Then, using the method and equations outlined in Section 4.2, the module calculates each EV charging profile and sums up to obtain the total EV charging load. The Monte Carlo simulation repeats the above process until a targeted number of iterations is met (iterations = 25; see Figure 7). The total load is the final EV charging load (that is, the average of EV loads generated from each iteration) plus the base load. By summing up the final EV charging load and the base load, the total load can be obtained to evaluate EV grid impacts.

Figure 7 | **The Unmanaged Charging Module Flowchart**



Notes: EV = electric vehicle; SOC = state of charge.

Source: WRI China authors.

4.3.2 The Managed Charging and V2G Modules

As stated in Section 4.1, the managed charging and V2G technologies have limited applicability—mainly in the use cases with relatively short charging durations and long parking dwell times.

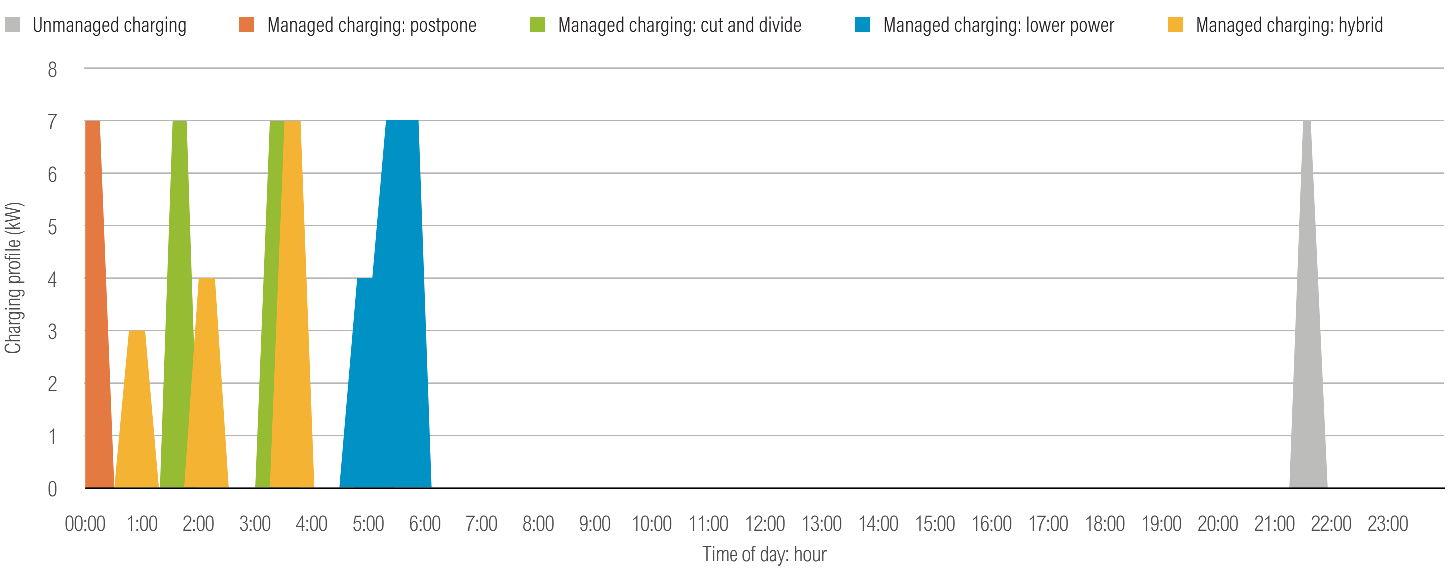
The two VGI modules employ both the Monte Carlo simulation and linear programming to derive optimal charging (or discharging) profiles that meet specific grid service objectives and EV travel demands. These objectives include avoiding large investments for distribution grid upgrades and ensuring that EVs are sufficiently charged (or sufficiently recharged after discharging) so that EV owners are ready for the next day's travel.

The flow of the two VGI modules is as follows: First, the Monte Carlo simulation is used to initiate the beginning state of each EV in the site. Then, the linear programming function creates an empty charging (or discharging) profile as the variable to be optimized (that is, $singleEV\_charge\_profile_{i,t}$ and $singleEV\_discharge\_profile_{i,t}$, as in Appendix C), and the charging (or discharging) profile for each EV (i) is determined at each time interval (t) within the arrival time and departure time, based on an optimization procedure. In other words, the optimization procedure of linear programming will dynamically control when individual EVs charge (or discharge) and how much power they use to charge (or discharge), including delaying or prioritizing an EV to charge later or earlier given each EVs specific travel demand. Figure 8 shows different possible charging profiles generated by the optimization procedure. By summing up all the EV loads, the total EV load and the impact on the grid can be obtained (Figure 9).

To create an optimization procedure, the linear programming function needs to establish one optimization objective function and a series of constraints. It also must employ a linear programming optimizer to solve for the optimized charging (or discharging) profile of each EV:

- The default objective function in the model is to minimize the difference between peak load and valley load on the transformer or the substation—that is, to flatten the total load curves by shaving the peak load and filling the valley load. As a result, not only can the distribution grid expansion be avoided due to peak shaving, but the costs for utilities and customers can be reduced because EVs are charging at the relatively cheap (valley) hours. But users can specify their own

Figure 8 | **Managed Charging Profiles for Individual EVs**



Notes: Hybrid includes the three different managed charging profiles combined—postpone, cut and divide, and lower power.

Source: WRI China authors.

objective function in the Python script; for example, if the objective of managed charging is to minimize utility costs, then the objective function can be specified to minimize the sum of the hourly utility cost (that is, the hourly load multiplied by the hourly utility rate) (Table 5).

- The model constraints applied to each EV help the optimizer search for the best VGI control strategy for the vehicle that will both meet the objective function and avoid interfering with the EV owner's travel demand. For example, if an EV has to leave earlier than usual, its parking duration (as specified by the model user) will be shorter, so the optimizer will automatically prioritize the car to charge early and possibly at a full power rating to meet its parking duration constraint.[8] Also, for managed charging and V2G, it is assumed that there is an infinite number of smart chargers (or V2G chargers) provided on the site; therefore, charger availability is not considered a constraint. The default model constraints are listed and explained in Table 6.

Only the Python script version of the simulator allows for tailoring the objective function and the constraints to a specific site (for an example, see Appendix C). When the tool is being used to control the charging of each car at a site (as opposed to being used as a simulator to estimate load), different arrival and departure times can be specified for individual cars in the Python script.

Table 5 | **Objective Functions to Be Selected by Different Stakeholders**

Stakeholders	Objective Functions
Transmission system operator	**Least increases in system peak load** (*Base load: system loads*) • Minimize difference between peak load and valley load • Minimize peak load
Distribution system operator	**Least investments on distribution upgrade** (*Base load: distribution loads*) • **Minimize local peak-valley load difference** • Minimize local peak load
EV user	**Least cost on utility tariffs** • Minimize utility cost = $\sum_{t=1:24}$ hourly load profile$_t$ × hourly utility tariff[a] • Minimize demand charge = peak load × demand charge

Notes: [a] The utility tariff can be fixed rate or time-of-use rate.

Source: WRI China authors.

Table 6 | **List of Constraints for Linear Programming**

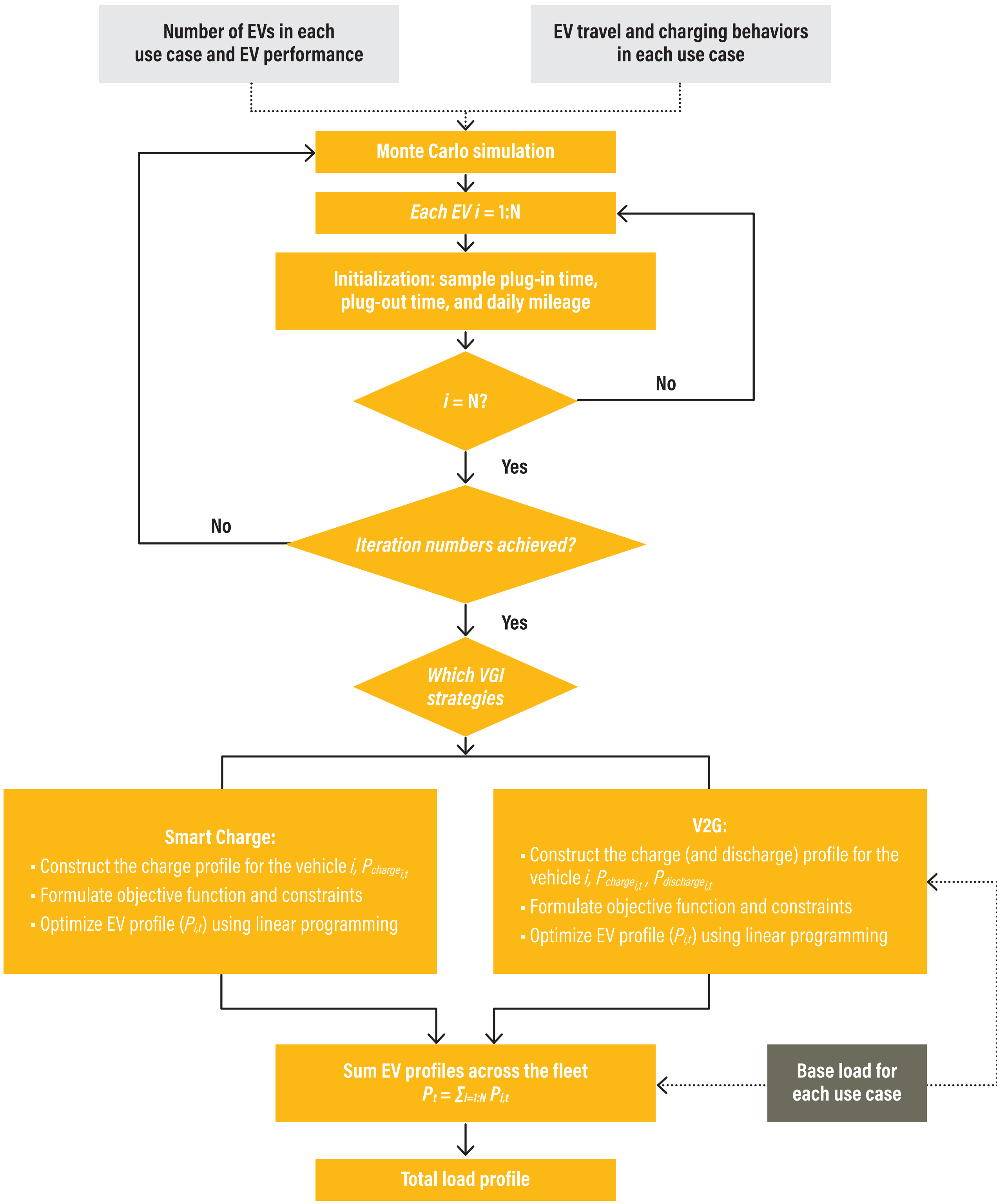
No.	Purpose of the Constraint	Equation and Defaults	Modules	Adaptability
1	Define EV's parking duration[a]	$t \in [starttime(i), starttime(i)+Parkingduration]$	Managed charging, V2G	√ (redefine parking duration)
2	Define upper and lower limits of charging (or discharging) power	$singleEV\_charge\_profile_{i,t} \in [3kW,7kW]$, $singleEV\_discharge\_profile_{i,t} \in [-7kW,-3kW]$	Managed charging, V2G	√ (redefine upper and lower limits)
3	Define charging starting state of charge (SOC)	$SOC_{i,starttime(i)} = StartSOC_i$	Managed charging, V2G	--
4	Update SOC at each time interval	$SOC_{i,t} = SOC_{i,t-1} + single\_charge\_profile_{i,t-1} \times (\phi/C) + single\_discharge\_profile_{i,t-1} * (k/C)$	Managed charging, V2G	--
5	Define charging end SOC	$SOC_{i,endtime(i)} = 100\%$	Managed charging, V2G	○
6	Define maximal depth of discharging	$SOC_{i,t} \geq 30\%$	V2G	○
7	Require that an EV cannot charge and discharge at the same time	$singleEV\_charge\_profile_{i,t} \times singleEV\_discharge\_profile_{i,t} = 0$	V2G	--

Notes: "√" indicates the constraint is tweakable in both the online application and the Python script. " ○ " indicates the constraint is only tweakable in the Python script. "--" indicates the constraint should be kept unchanged.

[a] A constant parking duration for all EVs is applied to reduce the model input burdens for users, but users can alter each EV's parking duration in the Python script.

Source: WRI China authors.

Figure 9 | **Flowchart of the Two VGI Modules**



Notes: EV = electric vehicle; LP = linear programming; VGI = vehicle-grid integration.

Source: WRI China authors.

4.4 Model Outputs

The model outputs include EV load and total load profiles.

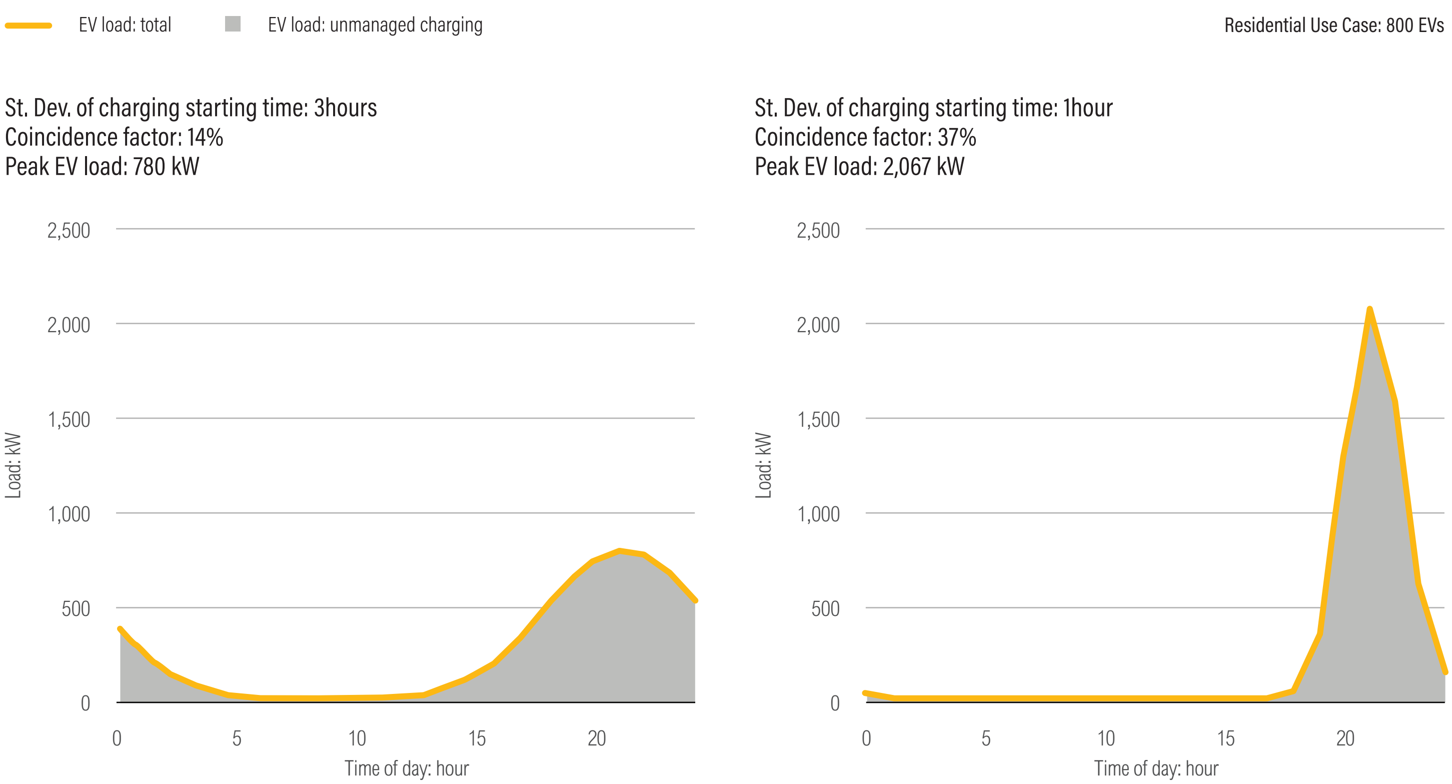
4.4.1 EV Load Profiles

EV loads at different locations and times of day provide insights into the features of this new customer load.

For utility companies, EV peak loads calculated using the coincidence factor (Equation 1) are sufficient to inform infrastructure expansion decisions. The coincidence factor, the reciprocal of the diversity factor, reflects the maximal number of EVs that can charge simultaneously in different use cases.

The higher the coincidence factor, the greater the impact EVs are likely to exert on the electric grid. Since EV loads are a new type of customer load, the coincidence factors of existing customer loads may not apply. The coincidence factors derived from this model are instrumental for determining their values. For example, preliminary results show that the coincidence factors of EV charging are highly variable and are particularly correlated with travel behaviors such as arrival time. If EV arrival times to the site are concentrated within 2 hours, the coincidence factor could be as high as 35–40 percent (Figure 10). However, if the arrival times for most of the EVs are spread within 6 hours, the coincidence factor could drop to around 14 percent.

Figure 10 | **Relationships among EV Load, Coincidence Factor, and Charging Starting Time**



Notes: EV = electric vehicle; St. Dev. = standard deviation. “EV load: total” is the sum of the unmanaged charging load, managed charging load, and V2G load. In the unmanaged charging module, the “EV load” equals the unmanaged charging load. The model assumes that the charging starting time in the Residential Use Case by default follows the normal distribution. Therefore, there is no charging event occurring during daytime hours.

Source: WRI China authors.

4.4.2 EV Load Impacts

The total load profile—the sum of the EV charging load and the base load—provides a full picture of EV load impacts. Based on the total load profiles, the key concerns of utility companies, such as the overloading problem and the utilization efficiency of transformers (or substations), can be answered (Table 7):

- **Overloading.** Output indicators, such as peak load and the utilization factor, are instrumental for examining if the peak load demand exceeds the rated capacity of the transformer (or substation). In fact, the limit set for grid expansion varies from country to country. For example, China would usually cap the limit at 80 percent of the rated capacity, whereas other countries would cap at 100 percent of the rated capacity. In the model output, besides the rated capacity, the model output gives a warning at 80 percent of the rated capacity to alert users that the transformers are approaching the point for expansion.
- **Utilization efficiency.** The output indicator for the peak-valley load difference is used to evaluate if the investments on electrical resources (from generation, transmission, and distribution) are utilized efficiently. The higher the difference, the more capacity is required for the transformer (or substation) to accommodate the same energy demand. Also, it becomes less cost-effective to operate the grid system; hence, the utilization of the devices is inefficient.

Figure 11 presents an example of the Residential Use Case. The charts in the first row display EV loads under different charging strategies, and those in the second row show the overall load impacts on the substation. Under unmanaged charging, the peak load is 234 kW over the rated capacity (4,000 kW) of the substation. Not only will the substation be overloaded, but the higher load demand will also lead to inefficient use of the transformers in the substation. This is because the peak power demand occurs for only one to two hours a day, and then the demand drops to and maintains a very low level for the rest of the day. However, with 60 percent of the EVs participating in managed charging (the other 40 percent keep performing unmanaged charging[9]), the peak load is flattened, and some EV charging load is shifted to the off-peak night hours.

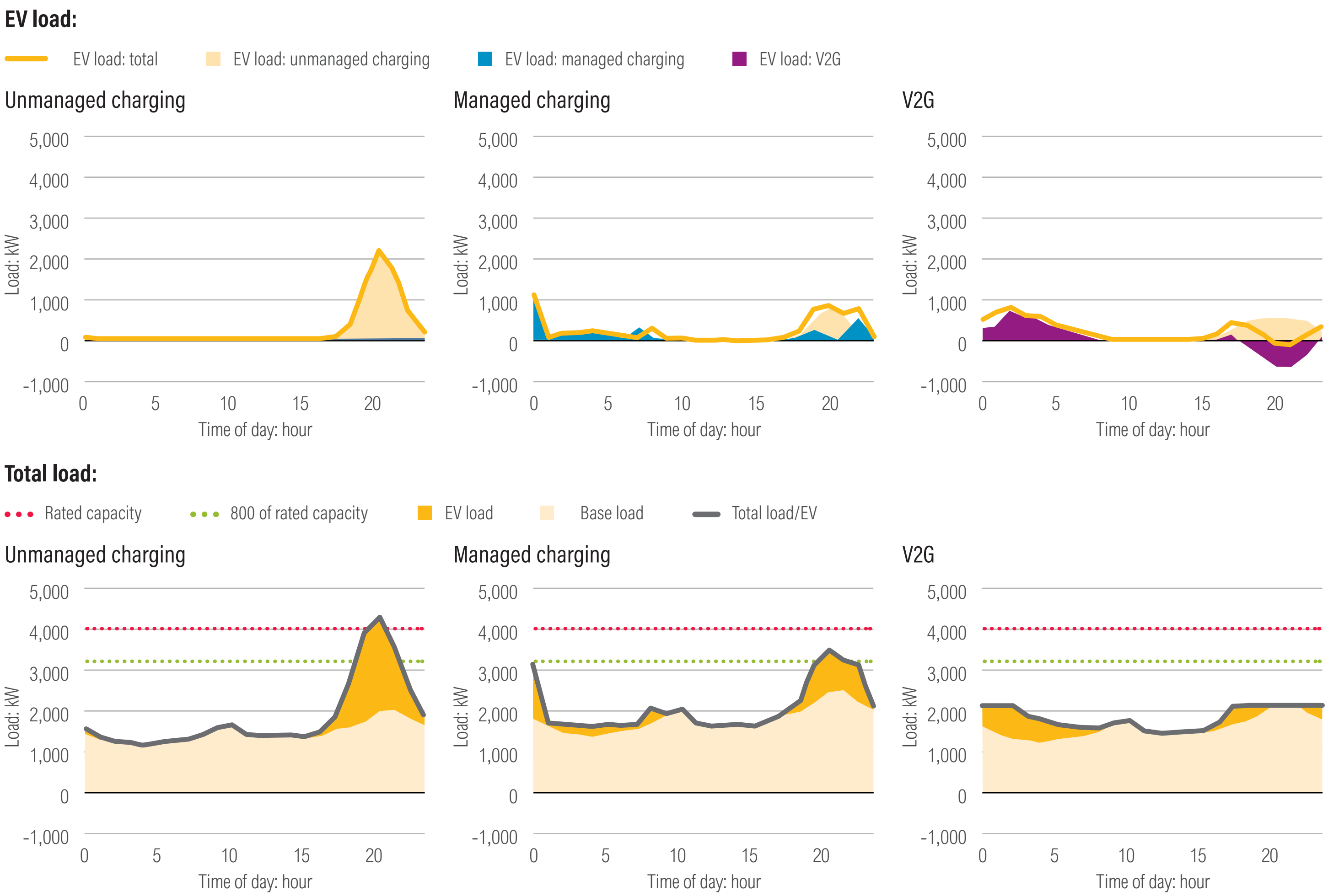
Table 7 | **Model Output Indicators and Calculation Equations**

	Output Indicator	Explanation	Equation	Limit for Grid Expansion
Overloading	Peak load (maximum hourly load)	Maximum hourly total load	peak load = $\max_{t=1:24}(\text{total\_load}_t)$	80–100% × rated capacity
	Utilization factor	Ratio of peak load to the capacity of the transformer(s)	utilization = peak load / rated capacity	80–100%
	EV ratio in peak load	Ratio of EV load in the peak load	$EV_{ratio} = \text{EV\_load}_{max\_t}$ / peak load	--
Utilization inefficiency	Peak-valley load difference	Difference between peak total load and valley total load	valley load = $\min_{t=1:24}(\text{total\_load}_t)$ diff = peak - valley	--

Source: WRI China authors.

Figure 11 | An Example of EV Load Impacts in a Residential Use Case

Residential Use Case: 800 EVs, 800 chargers



	Unmanaged Charging	Managed Charging	V2G
EV enrollment	• Unmanaged charging: 800 EVs	• Unmanaged charging: 480 EVs • Managed charging: 320 EVs	• Unmanaged charging: 640 EVs • V2G: 160 EVs
Utilization factor (%)	106	76	53
Peak load (kW)	4,234	3,044	2,127
EV ratio in peak load (%)	49	--	--
Peak-valley difference (kW)	3,034	1,610	693

Notes: EV = electric vehicle; V2G = vehicle-to-grid. “EV load: total” is the sum of the unmanaged charging load, managed charging load, and V2G load. In the unmanaged charging module, the “EV load” equals the unmanaged charging load.

Source: WRI China authors.

5. HOW TO USE THE MODEL

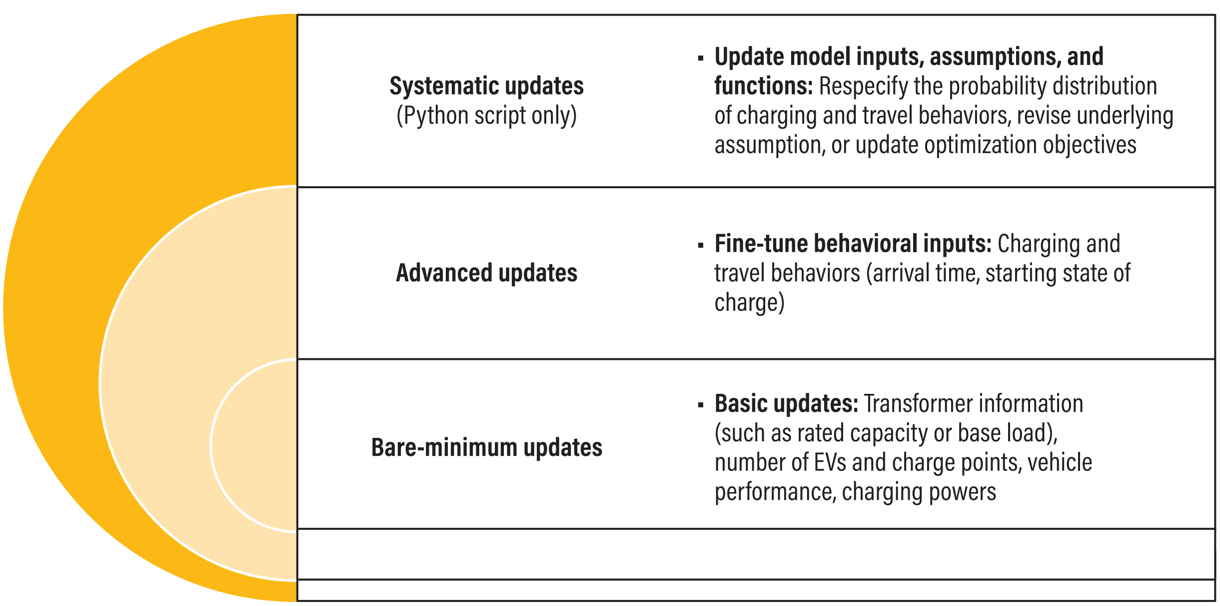
5.1 Model Input and Function Updates

Although the simulator offers default inputs, location-specific updates are necessary to contextualize the model. The following provides tiered options to update the model (Figure 12):

- If users do not have information on daily EV travel and charging patterns, the model's default values are sufficient to perform a rough estimation of EV load impacts. The bare-minimum updates required for the model include the number of EVs, vehicle technical specifications, the number of chargers, charging power rates, and local transformer (or substation) information (including daily base load and rated capacity).
- If users have access to rough estimates of charging and travel patterns through charging point operators, vehicle OBD systems, or community surveys (see Section 4.2), additional updates can be made. These updates include tailoring vehicle arrival times and the charging starting SOC.
- If users have thorough information on charging and travel behavior and would prefer additional functions beyond what are offered by the web application, they can work with the Python script to redefine the behavioral inputs (e.g., respecifying the daily mileage distribution, changing the normal arrival time distribution into other best-fit distributions, or refining an individual EV's departure time), change the model assumptions, or improve the model functions by revising the optimization objective and constraints.

To demonstrate how to use the online tool to perform both the bare-minimum and advanced updates, two examples are given here. Users who are interested in tweaking the Python scripts for extended functions and better flexibility, please refer to Appendix C.

Figure 12 | **Tiered Updates on the Simulator**



Source: WRI China authors.

Table 8 | **Functional Differences between the Web Application and the Python Script**

	Web Application	Python Script
Modules		
Modules	• Unmanaged charging • Managed charging	• Unmanaged charging • Managed charging • V2G
Model inputs		
Distribution of daily mileage	Fixed lognormal distribution that cannot be changed	Any type of probability distribution defined by model users
Distribution of arrival time and starting state of charge (SOC)	Normal distribution; users can change the means and the deviations	Any type of probability distribution defined by model users
Parking duration	One value defined by model users[a]	Any value defined by model users or any type of probability distribution defined by model users
Model assumptions		
End SOC	100%	Any value defined by model users or any type of probability distribution defined by model users
Charging or discharging efficiency	90%	Any value defined by model users
Maximum depth of discharging	30%	Any value defined by model users
Number of managed chargers or V2G chargers	Indefinite	Subject to model users' specifications
Functions		
Optimization objective	Fixed (minimize peak-valley difference)	Subject to model users' specifications
Constraints	Fixed	Subject to model users' specifications

Notes: SOC = state of charge; V2G = vehicle-to-grid.

[a] For simplicity, the web application allows for the tailoring of a single parking duration value applied to all electric vehicles. If more fine-grained parking duration information can be gathered, the constraint should be revised in the Python script.

Source: WRI China authors.

5.1.1 Example 1: Bare-Minimum Updates Using the Web Application

With the increasing adoption of EVs in residential neighborhoods, distribution substations risk being overloaded. Distribution system operators who are responsible for planning grid expansion need to understand when the capacity of distribution substations will become insufficient. To solve the problem, users need to use the **unmanaged charging module in the Residential Use Case.**

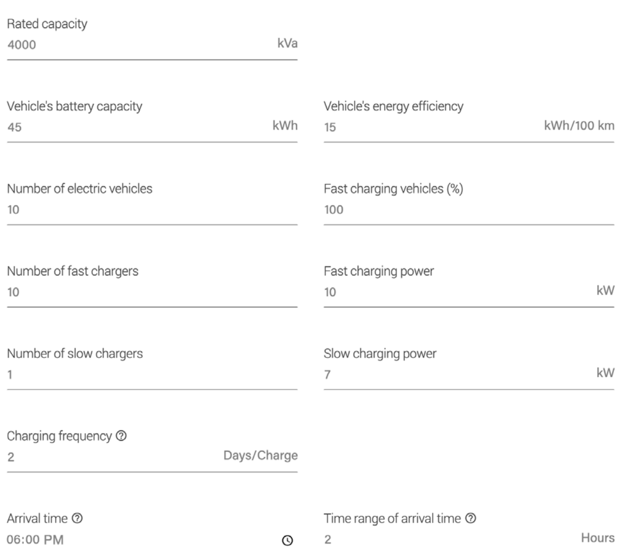
To ease the input burdens for users, the model inputs are simplified into the features of an average EV. For example, the online tool assumes that the average EV battery capacity in a neighborhood setting is around 45 kWh and the average efficiency is 15 kWh/100 km in 2020. The arrival time and the time range are the mean and deviation used to fit a normal distribution—that is, assuming the arrival times of the EVs follow the normal distribution with the mean time at 18:00 and one-hour deviation in 2020.

Numerous uncertainties exist in the future. Users can assume that in 2025 the number of EVs in the neighborhood will increase to 400 and average battery capacity and energy efficiency will change to 50 kWh and 13 kWh/100 km, respectively. Other potential future changes are listed in Figure 13.

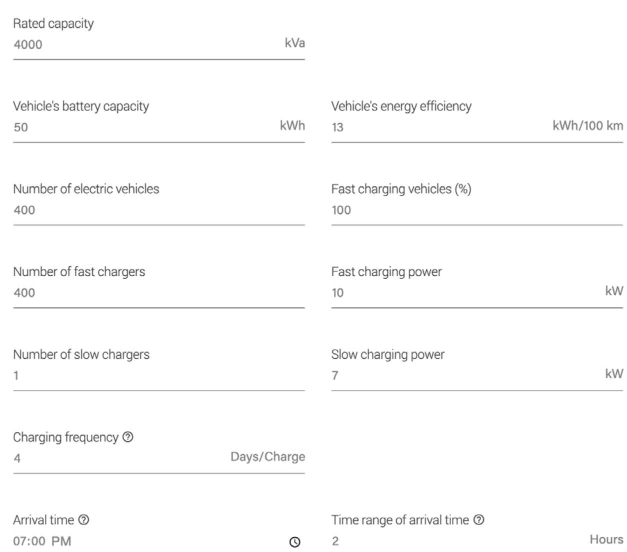
Figure 13 | **Model Inputs for Example 1**

	2020	2025
Number of EVs	10	400
Vehicle battery capacity	45 kWh	50 kWh
Energy efficiency	15 kWh/100 km	13 kWh/100 km
Charging frequency	2 days per charge	4 days per charge
Arrival time	18:00	19:00
Time range of arrival time	2 hours	2 hours

a. Inputs for 2020


Rated capacity
4000 kVa
Vehicle's battery capacity
45 kWh
Vehicle's energy efficiency
15 kWh/100 km
Number of electric vehicles
10
Fast charging vehicles (%)
100
Number of fast chargers
10
Fast charging power
10 kW
Number of slow chargers
1
Slow charging power
7 kW
Charging frequency
2 Days/Charge
Arrival time
06:00 PM
Time range of arrival time
2 Hours

b. Inputs for 2025


Rated capacity
4000 kVa
Vehicle's battery capacity
50 kWh
Vehicle's energy efficiency
13 kWh/100 km
Number of electric vehicles
400
Fast charging vehicles (%)
100
Number of fast chargers
400
Fast charging power
10 kW
Number of slow chargers
1
Slow charging power
7 kW
Charging frequency
4 Days/Charge
Arrival time
07:00 PM
Time range of arrival time
2 Hours

Note: EV = electric vehicle; kVa = kilovolt-ampere.

Source: WRI China authors.

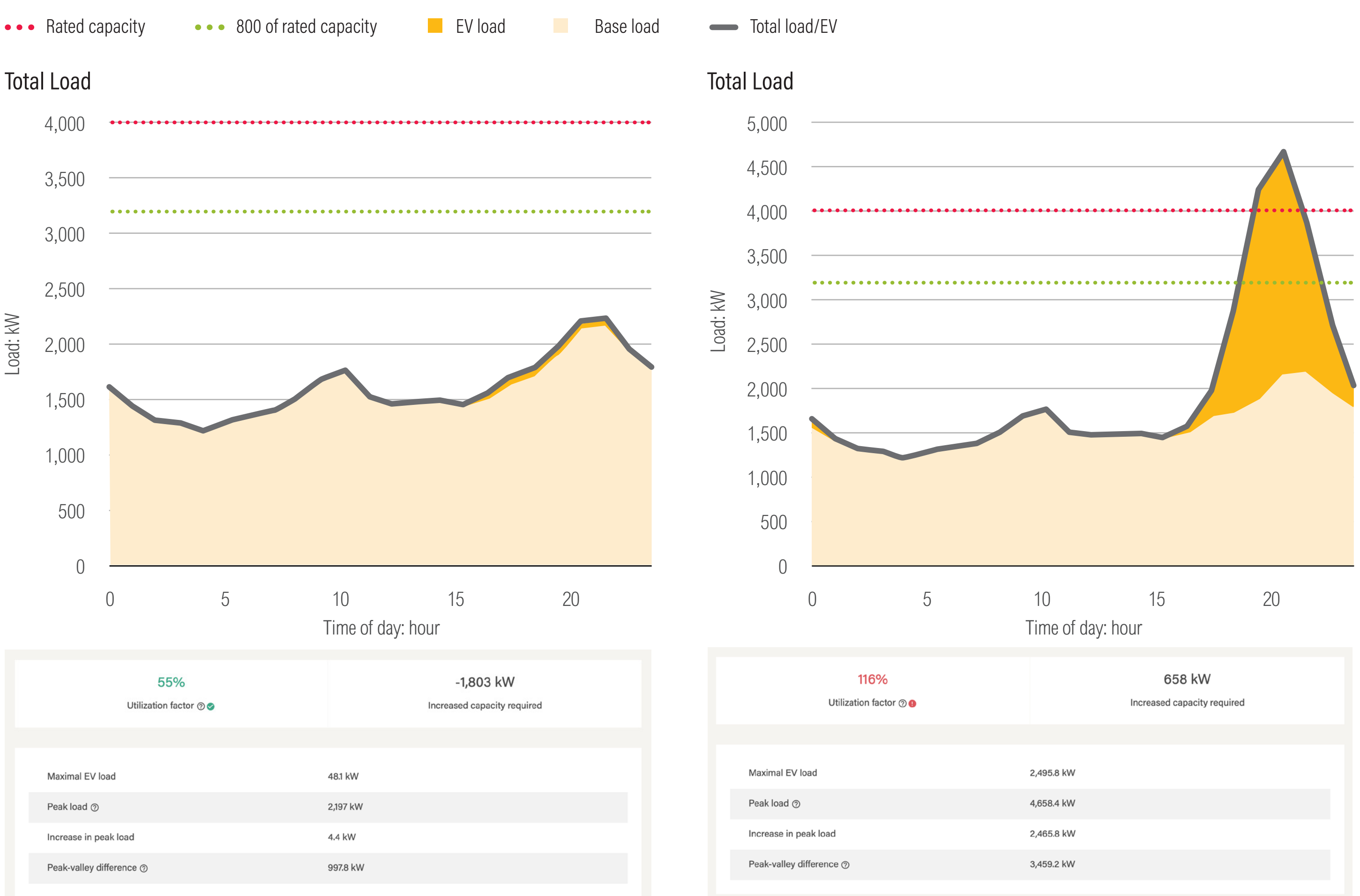
Figure 14 shows the results from using the above inputs to run the model twice and comparing the results from these two runs. With the increase in EV stocks in 2025, the EV charging load will become the major residential load, especially from 17:00 to 00:00. This increase in EV charging load will overload the substation, with the 4,658 kW peak load exceeding the current rated capacity of 4,000 kVa. If no managed charging strategies are deployed, the substation will require a capacity increase of 658 kW to accommodate the EV charging load.

5.1.2 Example 2: Premium Updates Using the Web Application

For freight operators, the electrification of freight fleets could lead to costly upgrades of the distribution grid because most EVs tend to return to a depot and be charged at the same time. However, if using managed charging to stagger the charging time and optimize the charging power of the electric fleet, the costly grid expansion can be avoided. This corresponds to a new use case: unmanaged charging and managed charging in the User-Defined Use Case.

To create a new use case for the freight operator example, the following inputs need updates (Figure 15).

Figure 14 | **Model Outputs of Example 1**



Note: EV = electric vehicle. The model assumes that the charging starting time in the Residential Use Case by default follows the normal distribution. Therefore, there is no charging session occurring during daytime hours.

Source: WRI China authors.

The arrival time and starting charging SOC of the fleet will need to be revised based on the operation schedule. Here, this example assumes the arrival time of the fleet is concentrated around 18:00 and follows a normal distribution with a two-hour deviation. The mean of the starting charging SOC for the fleet is 40 percent, with a 20 percent deviation. Furthermore, the use case assumes that the fleet depot has dedicated transformers (base load = 0) and the rated capacity of the transformers can accommodate no more than 60 charging points, with a maximum charging power output of 40 kW. The number of charging points is lacking in comparison to the 150-vehicle fleet size.

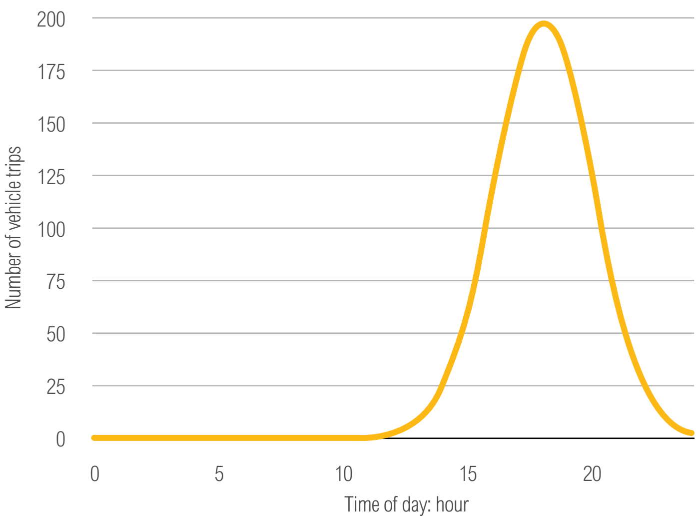
To compare the effects of managed charging, users need to run the tool under both unmanaged charging and managed charging and compare the results from the two runs.

Figure 15 | **Model Inputs of Example 2**

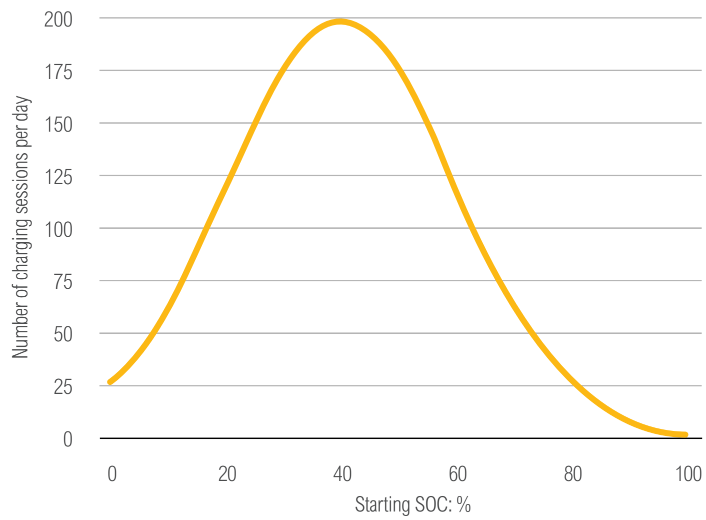
	Unmanaged Charging	Managed Charging
Vehicle battery capacity	150 kWh	150 kWh
Energy efficiency	75 kWh/100 km	75 kWh/100 km
Number of EVs	150	150
Number of chargers	60	60
Charging power	40 kW	--
Average charging starting SOC	40%	40%
Range of starting SOC	40%	40%
Arrival time	18:00	18:00
Time range of arrival time	4 hours	4 hours
Vehicles participating in managed charging	--	80%
Parking duration	--	8 hours
Charging power upper limit	--	40 kW
Charging power lower limit	--	10 kW

Figure 15 | Model Inputs of Example 2: (cont.)

Arrival time
Normal distribution
Mean: 18:00, St. Dev.: 2hours



Charging starting SOC
Normal distribution
Mean: 40%, St. Dev.: 20%



Rated capacity
2000 kVa

Vehicle's battery capacity
150 kWh

Vehicle's energy efficiency
75 kWh/100 km

Number of electric vehicles
150

Number of chargers
60

Charging power
40 kW

Average starting SOC
40 %

Potential range of starting SOC
40 %

Arrival time (default)

Arrival time (customized)

Arrival time
06:00 PM

Time range of arrival time
4 Hours

Enable managed charging?

Vehicles participating in managed charging (%)
80

Parking duration
8 Hours

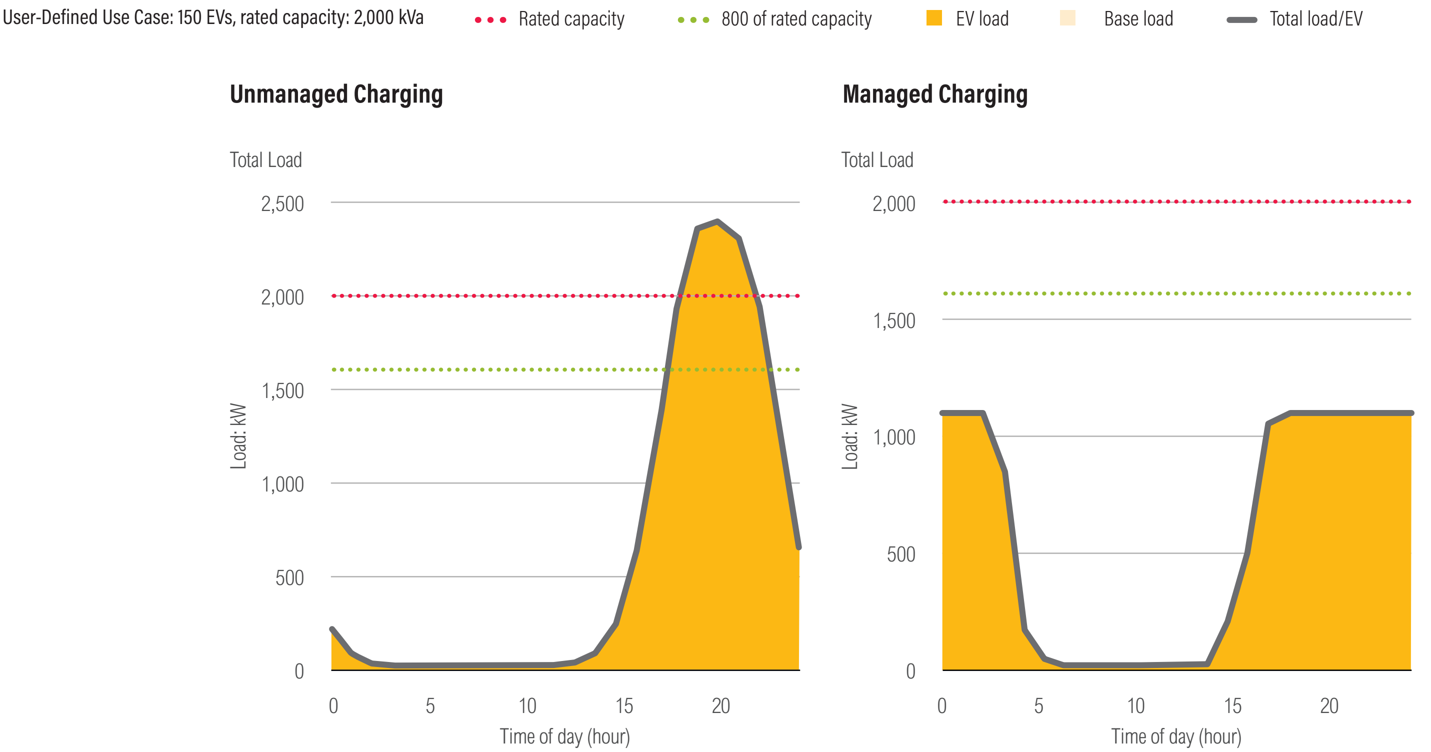
Charging power upper limit
40 kW

Charging power lower limit
10 kW

Note: EV = electric vehicle; SOC = state of charge; St. Dev. = standard deviation.

Source: WRI China authors.

Figure 16 | **Model Outputs of Example 2**



	Unmanaged Charging	Managed Charging
Peak load	2,369 kW	1,094 kW
Utilization factor	120%	55%

Note: EV = electric vehicle.

Source: WRI China authors.

Under unmanaged charging, the modeled peak load is 2,396 kW, exceeding the 2,000 kVa rated capacity of the transformer. Because of the lack of charging facilities, the average waiting time for each freight vehicle to be charged is nearly five hours. However, if deploying managed charging, the peak load can be reduced. Considering that public acceptance of managed charging and V2G is still limited at the early stage of the adoption, users are encouraged to specify a fraction of EVs to participate in managed charging or V2G in the VGI modules (the default value is set at 10 percent), with the rest of the EVs continuing to use unmanaged charging. In this example, assuming 80 percent of the fleet participates in managed charging, the managed charging power fluctuates between 10 kW and 40 kW, the model results show that the peak load is shaved to 1,094 kW (Figure 16). Compared to the unmanaged charging, the peak load reduces by 53 percent, and the optimized load curve is flattened. This occurs without affecting the daily operation of the fleet.

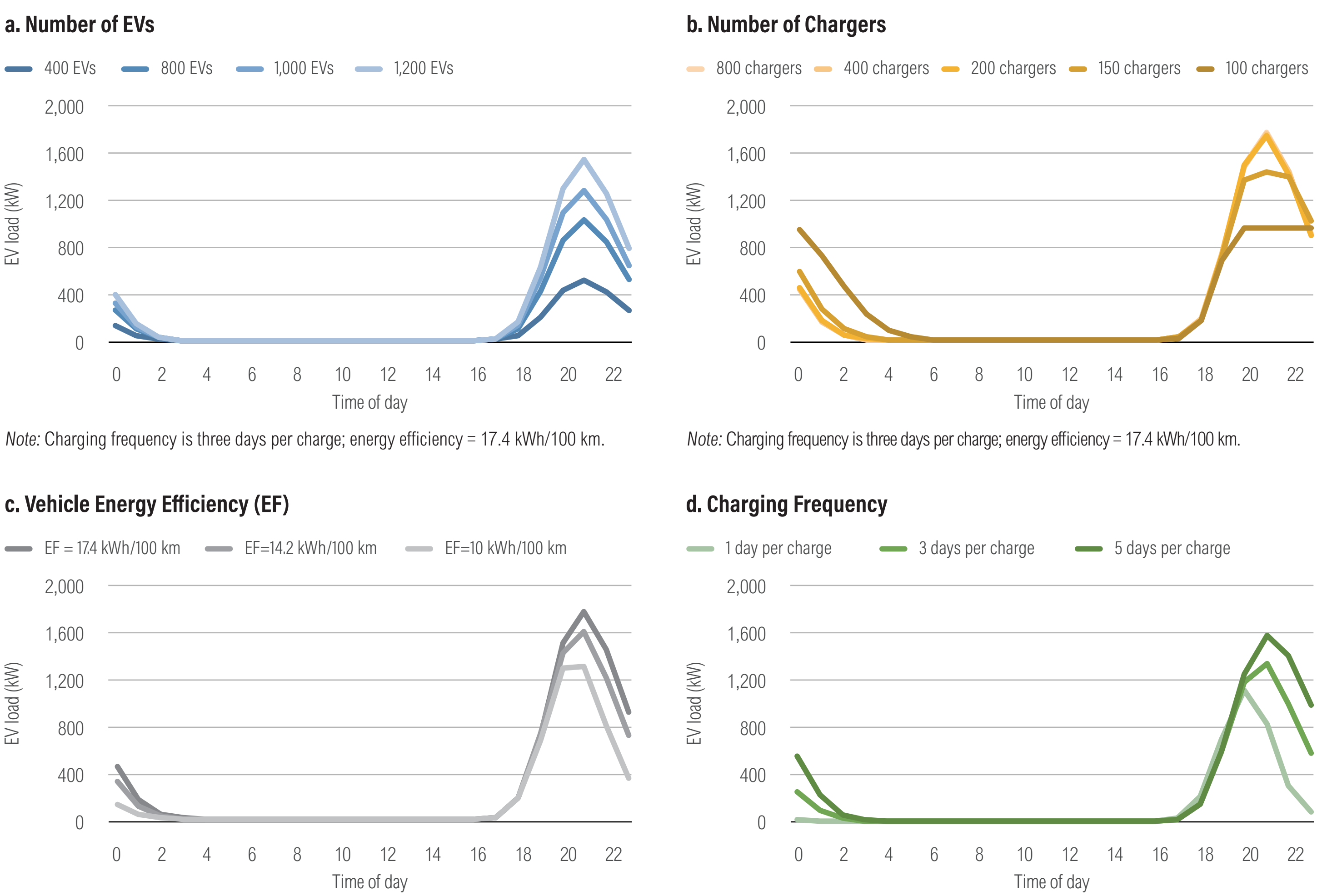
5.2 Sensitivity of Model Inputs

Numerous model inputs have a bearing on EV load impacts. For users who aim to forecast long-term EV load impacts, the following shows how the future technology advances or behavior changes in selected variables will affect EV charging loads (Figure 17).

- **Vehicle electrification**. The increased number of EVs will be the key influencing factor on EV grid impacts.
- **Number of chargers.** The shortage of charging facilities will cap EV charging loads and reduce EV grid impacts (but will also slow the rate of vehicle electrification).
- **Vehicle energy efficiency.** When EVs become more energy efficient, the energy they draw from the grid will be less, and the overall EV loads will drop.
- **Charging frequency.** When EV battery ranges increase and drivers charge EVs less often, EVs will tend to draw more energy from the grid at each charging session. If the coincidence factor keeps constant, the EV load will grow significantly.

Figure 17 | **Sensitivity Analysis of Vehicle Energy Efficiency, Charging Frequencies, and the Number of Chargers under Unmanaged Charging**

Residential Use Case: 800 EVs



Note: EV = electric vehicle.

Source: WRI China authors.

6. LIMITATIONS

Although the simulator can capture and model most of the use cases, it has a number of limitations.

The simulator is inadequate to model vehicles that charge more than once a day. This is because it is difficult to characterize model inputs such as arrival time and charging starting SOC when EVs charge frequently within a day. The EVs that charge more than once a day are typically operating fleets, and because fleet operators follow strict operation schedules, their grid impacts can be calculated based on the operation schedules. Also, to obtain optimal load results for some operating fleets, operational schedules will need to be adjusted to optimize vehicle arrival and departure times. Users can refer to dedicated software like HASTUS to perform this type of optimization.

APPENDIX A. MODEL VARIABLES

Table A1 shows the matrix of the model input variables. It is noteworthy that all of the model variables listed in the table are tailorable by users. The model variables also vary by use cases and charging strategies; for example, Level 1 chargers (slow chargers) are not common for the Office and Public Use Cases.

Table A1 | **Model Inputs by Use Cases and Modules**

Variable	Unit	Data Type	Applicability	Residential	Office	Public	User-Defined
Base load	kW	24-item array	All the modules	√	√	√	√
Rated capacity	kVa	Single number	All the modules	√	√	√	√
Battery capacity of the vehicle	kWh	Single number	All the modules	√	√	√	√
Vehicle energy efficiency	kWh/100 km	Single number	All the modules	√	√	√	√
Number of electric vehicles (EVs)		Single number	All the modules	√	√	√	√
Percentage of fast charging vehicles	%	Single number	All the modules	√	--	--	--
Number of fast chargers (Level 2 and above)	N/A	Single number	All the modules	√	√	√	√ (Includes all types of chargers)
Number of slow chargers (Level 1)	N/A	Single number	All the modules	√	--	--	--
Fast charging power	kW	Single number	All the modules	√	√	√	√ (Includes all types of chargers)

Table A1 | **Model Inputs by Use Cases and Modules (cont.)**

Variable	Unit	Data Type	Applicability	Residential	Office	Public	User-Defined
Slow charging power	kW	Single number	All the modules	√			
Charging frequency	Days	Single number	All the modules	√	√		
Arrival time	Time	Normal distribution: average and deviation; 24-item array	All the modules	√	√	√	√
Charging starting state of charge	%	Normal distribution: average and deviation; 24-item array	All the modules	--	--	√	√
Daily mileage	km	Single number	All the modules	○	○	--	--
Solar curve	kW	24-item array	All the modules	√	√	√	√
Percentage of EVs that participated in managed charging/ V2G	%	Single number	VGI modules only	√	√	√	√
Parking duration	Hours	Single number	VGI modules only	√	√	√	√
Charging power upper limit	kW	Single number	VGI modules only	√	√	√	√
Charging power lower limit	kW	Single number	VGI modules only	√	√	√	√

Note: kVa = kilovolt-ampere; VGI = vehicle-grid integration; V2G = vehicle-to-grid. "√" indicates the variable is the required input; " ○ " indicates the variable is an optional input and is only tweakable in the Python script; "--" indicates the variable is nonexistent in the use case.

Source: WRI China authors.

APPENDIX B. MODEL KEY ASSUMPTIONS

The model also relies on the following assumptions (Table B1) based on existing studies (INL 2015; Xue et al. 2020). However, users can also tweak the values of the variables in the Python script.

Table B1 | **Model Assumptions (or Fixed Variables)**

Variable	Unit
Charging ending state of charge	100%
Charging energy efficiency	90%
Discharging energy efficiency	90%
Maximum depth of discharging	30%
Number of managed chargers or vehicle-to-grid (V2G) chargers	Indefinite

Source: WRI China authors.

APPENDIX C. EXTENDED FUNCTIONS OF THE PYTHON SCRIPTS

The Python script offers greater flexibility. Model users can simulate V2G's load-shifting effects and also tailor all the model inputs, the model assumption, and specific functions in the Python script.

The following presents an example of how to revise the objective function and constraints under the V2G strategy in the Python script.

First, the objective function is revised from "minimize the peak-valley differences" to "minimize the demand charge." A common demand charge scheme is applied here in which the demand charge is imposed on the peak load with a fixed rate of US$15/kW ($singleEV_charge_profile_{i,t}$ and $singleEV\_discharge\_profile_{i,t}$ are the optimized variables).

Minimize demand charges = *local peak load × $15/kW*

$$\text{Local peak load} = max_{t=0:24}\,(base\ load_t + EV\_charge\_load_t + EV\_discharge\_load_t)$$

$$EV\_charge\_load_t = \sum_{i=1:Veh} singleEV\_charge\_profile_{i,t}$$

$$EV\_discharge\_load_t = k \times \sum_{i=1:Veh} singleEV\_discharge\_profile_{i,t}$$

N is 24 hours in a day with 1-hour intervals
Veh is the total number of EVs in the use case
$singleEV\_charge\_profile_{i,t}$ and $singleEV\_discharge\_profile_{i,t}$ are, respectively, charge power and discharge load of vehicle *i* at time *t*
k is discharge efficiency (90 percent)

Second, the constraints are updated, including modifying the end SOC from 100 percent to 80 percent and adding a new constraint—the shortage in the number of V2G chargers.

Subject to

1) $SOC_{i,starttime(i)} = StartSOC_i$

2) $SOC_{i,t} = SOC_{i,t-1} + single\_charge\_profile_{i,t-1} \times (\varphi/C) + single\_discharge\_profile_{i,t-1} \times (k/C)$

3) $SOC_{i,t} \geq 30\%$

4) $SOC_{i,endtime(i)} = 80\%$

5) $singleEV\_charge\_profile_{i,t} \times singleEV\_discharge\_profile_{i,t} = 0$

6) $t \in [starttime(i), endtime(i)]$

7) $singleEV\_charge\_profile_{i,t} \in [3kW,7kW]$, $singleEV\_discharge\_profile_{i,t} \in [-7kW,-3kW]$

8) *for each time t*, $\sum_i SingleEV\_chargestate_{i,t} \leq n\_V2G\_chargers$ *(the number of V2G chargers is imposed as a constraint)*

where *starttime(i), endtime(i)* are, respectively, vehicle *i*'s arrival time and departure time; $SOC_{i,t}$ is vehicle *i*'s SOC state at time *t*; φ is charging efficiency; and *k* is discharge efficiency.

ABBREVIATIONS

DC	direct current
DSO	distribution system operator
EV	electric vehicle
eVKT	electric vehicle kilometers traveled
ICE	internal combustion engine
kVa	kilovolt-ampere
kWh	kilowatt-hour
OBD	onboard diagnostic
SOC	state of charge
TOU	time of use
VGI	vehicle-grid integration
VKT	vehicle kilometers traveled
V2G	vehicle-to-grid
V2G-Sim	Vehicle-to-Grid Simulator

ENDNOTES

1. *Facility owners* refers to energy managers of parking lots, industrial zones, commercial and office properties, or bus/logistic vehicle parking depots.

2. A distribution substation often includes a set of transformers.

3. EVs can charge during off-peak time periods, when the retail electric energy price is low, and discharge the energy during peak time periods, thereby reducing the costs of electricity.

4. For more about the V2G-Sim model structure, see http://v2gsim.lbl.gov/overview/model-structure.

5. EV batteries are commonly discharged to about 10–30 percent of the state of charge (SOC); fully depleting the batteries for each discharge cycle will accelerate battery degradation.

6. The energy efficiency of an EV is expressed as energy consumed per 100 kilometers traveled.

7. For managed charging and V2G, charging duration is enveloped by parking duration.

8. However, if the departure time is too early to allow for the vehicle to be fully charged, the constraint should be modified from 100 percent end SOC to less than 100 percent by the model user—the vehicle will not be charged fully given the limited parking duration. Alternatively, the EV owner could also opt out of the VGI measures, not to be included in the optimization process.

9. Considering that public acceptance of managed charging and V2G is limited at the early stage, the VGI modules allow users to specify a fraction of EVs to participate in managed charging or V2G, and the rest of the EVs remain using unmanaged charging.

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