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Validation of an Electric Vehicle Load Profile Simulation

Nicolas Sockeel[1], David Trinko[2], Rob Schurhoff[2], and Jennifer Kwong[2]

[1]Nicolas Sockeel (corresponding author) EPRI, Charlotte, NC 28262 USA, nsockeel@epri.com

[2]EPRI, Palo Alto, CA 94304 USA

Executive Summary

Electrification of road vehicles along with decarbonization of the electric power sector can provide substantial headway toward achieving net-zero carbon emissions by 2050. Utilities and car manufacturers alike are facing significant challenges in producing electric vehicles (EVs) and building charging infrastructure sufficient to serve the incoming new demand for EVs. To help with utility planning, EPRI has developed an EV load profile simulation tool that estimates current and future hourly power profiles that represent charging a population of EVs. The tool is designed to help utilities plan what future generation resources will be needed to provide the forecasted demand from the new EVs. The tool also evaluates different charge scheduling such as time-of-use (TOU) rates or avoidance of demand charges that can incentivize EV drivers to shift their recharging behavior. This paper describes the validation of the load profiles produced by the simulation tool compared to actual charging and trip data collected by EPRI and Southern Company during a study on passenger EV behavior in Southern Company's service territory.

Keywords: Electric vehicles, load management, passenger car, user behavior, utility.

1 Introduction

The proceedings of the sixth Intergovernmental Panel on Climate Change (IPCC) [1] highlight the increased concerns that scientists have toward the future consequences of climate change. As a response, many developed countries are pledging to reach net-zero carbon emissions by 2050 [2, 3]. In 2019, transportation was responsible for 17% of global greenhouse gas (GHG) emissions [4]. In developed countries, the share of transportation's contribution to GHG emissions is higher. In 2020, transportation represented approximately 27% of the United States CO_2 emissions [5]. Many publications confirm that transportation electrification can help reduce vehicle life-cycle carbon emissions [6–8], when the power to charge them is provided by low- or zero-carbon electricity, as shown in Figure 1. Consequently, the electrification of transportation has been identified as a key component of economy decarbonization. Many countries and original equipment manufacturers (OEMs) have pledged to produce only EVs by or before 2050 [8–10].

In the United States, McKinsey & Company has estimated that 48 million EVs could be on the road by 2030 compared to 3 million today [11] (see Figure 2). The electric grid will be impacted significantly by the shift from gasoline powered engines to EVs. In 2021, EVs in the United States consumed 11 TWh or 0.3% of the U.S. electricity production [12]. By 2030, the energy demand from EVs could rise to 230 TWh or 6.3% of the United States' energy production.

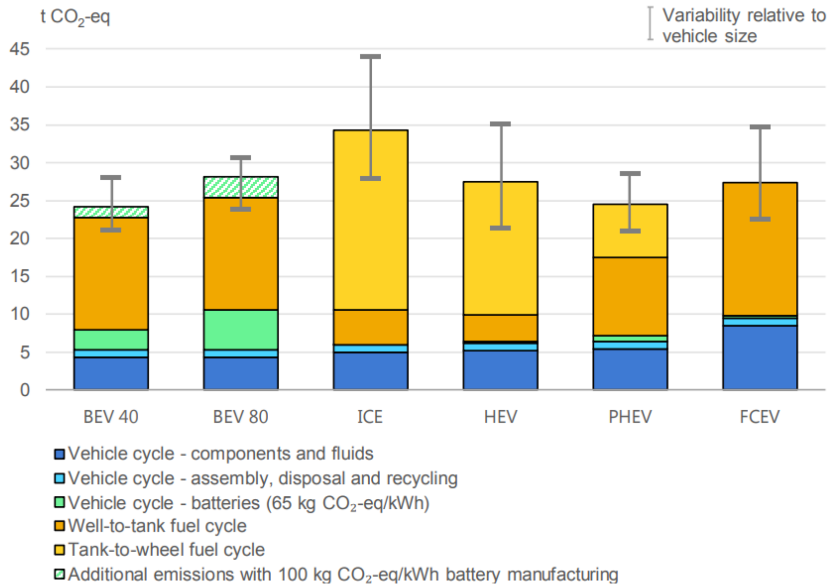

Figure 1: Comparative life-cycle greenhouse gas emissions over 10-year lifetime of an average mid-size car by powertrain [8]

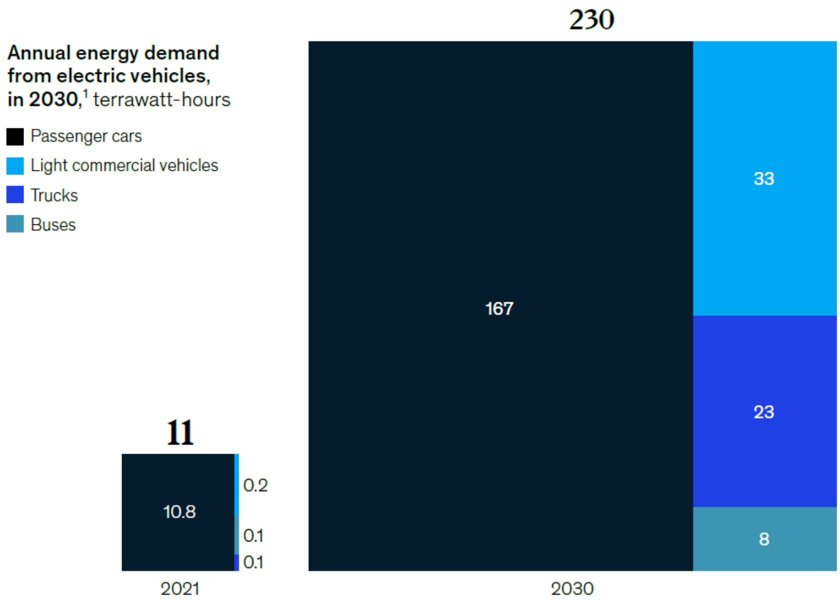

Figure 2: Annual energy demand of EVs from 2021 to 2030 in TWh [11]

Such an increase in energy demand from one sector represents a major challenge for utility companies because their infrastructure planning processes need to integrate the future energy demands from this large-scale electrification of transportation. To help utilities make informed choices on their future electric generation infrastructure, EPRI has developed an EV load profile simulation tool to estimate the current and future hourly load shape and magnitude that the electric grid will face with increased adoption of EVs. The tool can simulate a given population of EVs' charging load profile for different scenarios, including unmanaged charging, adoption of TOU rates, charge management strategies, and parameterized access to home, work, or public charge stations. Therefore, the tool provides crucial information to utility planning processes. Consequently, the main contributions of this paper are twofold. First, it provides insight about the load profile tool developed at EPRI. Second, the accuracy of the tool is validated through a comparison with real data on EV driving and charging behavior collected by EPRI and Southern Company during a study on passenger EVs within Alabama [13].

The remainder of the paper is as follows. In Section 2, the EV load profile tool is presented. In Section 3, the data collected on EV charging during the Southern Company passenger EV study is described. In Section 4, a comparison between the load profile tool simulation and the collected real data is provided. Finally, a conclusion is drawn in Section 5.

2 EV Load Profile Simulation Tool

Written in Python, the EV load profile tool's results are subject to a variety of parameters as well as some embedded assumptions. In brief, the simulation approach follows three steps:

1. Importing the survey data
2. Simulation phase
3. Aggregation phase

2.1 Importing survey data

The trip data used in the tool are based on household travel survey data, such as the National Household Travel Survey (NHTS) or the Puget Sound Regional Council's (PSRC's) regional survey. The simulation effectively converts conventional vehicle behavior into electrified equivalents and assumes that EVs will be driven the same way that conventional vehicles are driven. Table 1 shows the attributes needed to be present within the data.

Table 1: Information needed from the survey data

Parameter Name	Description	Example
Start time of day	Start date/time of the trip	10/1/2019 12:00:02 am
End time of day	End date/time of the trip	10/1/2019 3:50:14 am
Trip distance	Driven distance of a trip in miles	12.6
Vehicle ID	Identifier of a vehicle	73709ef4661681d43ed0
Day of week	Day of the week the trip occurs	Mon, Tue, …, Sun
Vehicle type	The type of vehicle	car, truck, MD, HD
Location	Where the trip starts	home, public, work
Survey weight	Number of drivers making this trip	512

2.2 Simulation phase

The purpose of the simulation step is to generate normalized charging profiles. *Normalized* means that the load profile represents the average contribution of a single vehicle to the total system-level load during a 24-hour period. Normalized profiles are simulated for each vehicle segment—one of many vehicle categories defined by parameters as explained next. Then, a scaled load profile per segment is calculated by scaling the normalized profile by the number of vehicles belonging to the segment, as shown in Figure 3. Segments are defined with the goal of capturing significant differences in charging behavior, for example, between vehicles that do or do not respond to TOU rates. Consequently, the definition of segments trades off reality with model complexity: with more segments, more assumptions need to be made and more load profiles per segment need to be generated.

The segmentation for passenger vehicles used in this paper is presented in Table 2. Each segment is defined by a combination of values from the Values column. For example, one segment is {EV type: BEV 150, Home charging: yes, Charge scheduling: time of arrival, Year: 2020, day type: weekday, Follow TOU: yes}. One full simulation is conducted for each segment, that is, for each branch of the tree drawn in Figure 3. Therefore, as more criteria are used, the amount of computation rises exponentially.

Table 2: Population segmentation

Criteria	Values	Criteria	Values
Year	2020	Follow TOU?	Yes, No
Home charging?	Yes	Day type	Weekday, weekend
Charge scheduling	Time of arrival (ToA), Time of departure (ToD)	EV type	PHEV 40; BEV 150, BEV 250

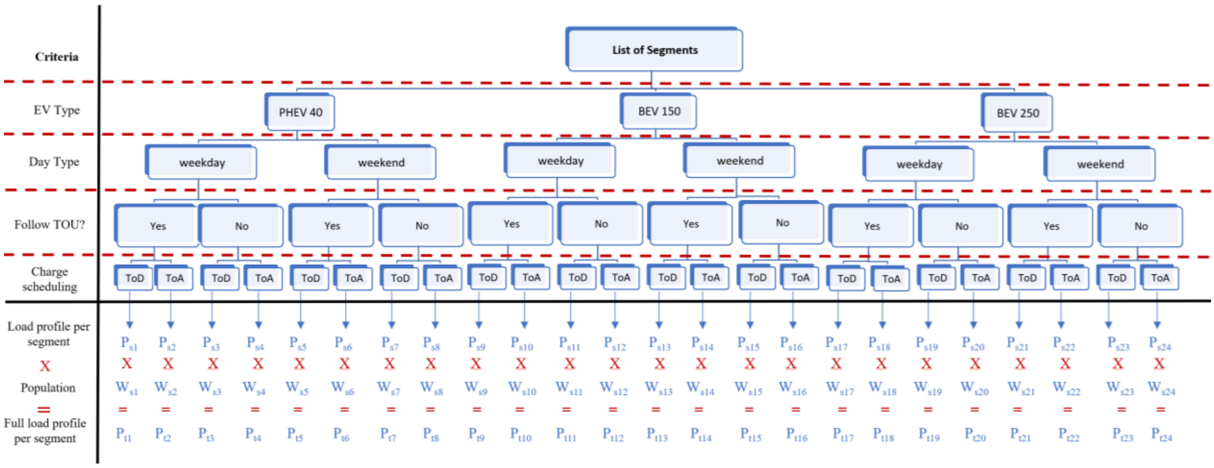

Figure 3: Segmentation process of the EV load profile tool

To compare simulation results against the data from the Southern Company passenger EV study, the simulation was configured to evaluate year 2020 only. Because the Southern Company passenger EV study data (referred to as *Southern data* hereafter) were obtained from actual EVs—rather than simulated from survey data—the assumptions underpinning the load profile tool had to be aligned with the study population. Within the Southern data, each vehicle has access to home charging. Moreover, the simulation option to consider the impact of ambient temperature on vehicle energy consumption is not used in this study. Instead, an average energy efficiency (energy consumption per mile) is used for each EV type based on the Southern data (cf. Sections 3 and 4).

2.3 Aggregation phase

The purpose of the aggregation step is to scale and combine normalized profiles to reflect a target population. The aggregation phase involves three distinct operations: addition, concatenation, and interpolation.

First, for any given day, the aggregate load profile is the sum of the scaled load profiles per segments for all the segments (addition). Second, the load profile over time is a sequence of individual days (concatenation). The yearly load profile output of the tool—an 8,760-hour load profile for each year of interest—is a concatenated sequence of summed load profiles per segment.

Finally, to generate load profiles for years that are not directly simulated (that is, not 2020, 2030, or 2040) and to simulate ambient temperature adjustments, the load profiles to which the addition and concatenation operations are applied are themselves obtained through interpolation. For example, a load profile for 2025 on a day that requires a temperature adjustment of 1.05 would be interpolated from the (year: 2020, 2030) and (temp adjustment: 1.0, 1.1) normalized load profiles.

For this study, only the year 2020 (the year in which the Southern data study occurred) was computed, and the temperature adjustment factor was set to 1. Therefore, no interpolations have been computed. Moreover, the Southern data sample of 135 drivers does not contain a large enough population to provide an insightful yearly (8,760 hour) load profile. However, the sample contributed a significant amount of daily data across the year that the drivers participated in the study. For validation, an average daily (24-hour) load profile was computed from the Southern data. The concatenation process was not evaluated in this validation effort because an 8,760-hour load profile was not generated.

3 Southern Company Data

The Southern Company data was sourced from a three-part study [13] on EV drivers within the three states in which Southern Company operates. The study collected and analyzed the EV charging and driving behavior of 135 participants in Alabama across an entire year. The aim was to understand EV charging behavior and the ensuing load profiles. The study provides insight into real-world operational characteristics of EVs, of which much data are not yet readily available. The remainder of this section describes the characteristics of the study's EV driver behaviors, including EV range, electric miles driven a year, and subscription to a TOU rate. Determining the characteristics of EV drivers is important for correctly parameterizing the load profile tool. The average power per vehicle and the energy consumption per location are compared with the load shape tool in the next section.

3.1 Population size

Figure 4 provides the distribution of vehicles participating in the Southern Company study. The outer ring shows the total number of vehicles in each representative group with corresponding labels identifying the vehicle groups and specifying the number of vehicles. The inner ring and the legend show how many vehicles of each vehicle model are present in the group and indicates which vehicle group each vehicle model falls under.

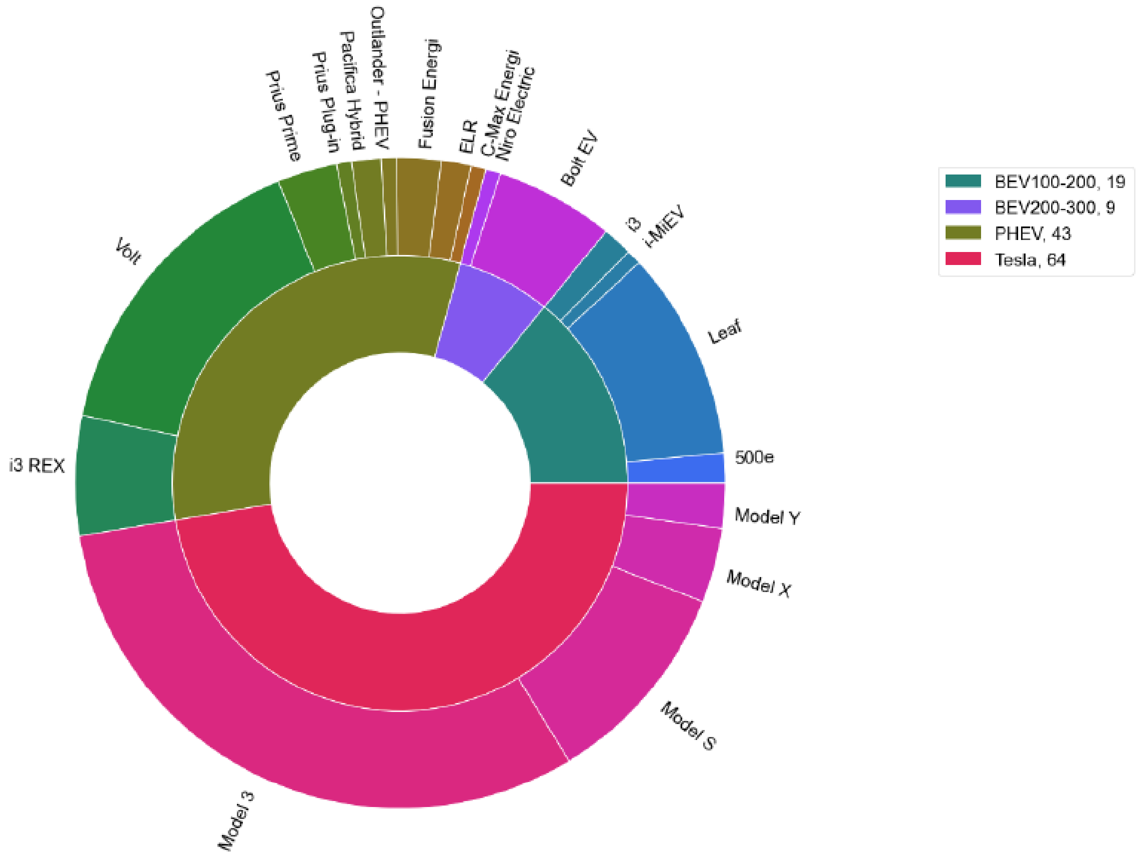

Figure 4: Distribution of vehicle models and groups from participating drivers

The EV load shape tool categorizes EV range as follows: plug-in hybrid EV (PHEV) 40, battery EV (BEV) 150, and BEV 250 mile range. Table 3 describes how the population of the study is split.

Table 3: Characteristics of the EV population

<table>
<tr><th colspan="2">Southern Data</th><th colspan="2">EV Load Profile Tool</th></tr>
<tr><td>Vehicle Type</td><td>Count</td><td>Vehicle Type</td><td>Count</td></tr>
<tr><td>PHEV</td><td>43</td><td>PHEV 40</td><td>43</td></tr>
<tr><td>BEV 100–200</td><td>19</td><td>BEV 150</td><td>19</td></tr>
<tr><td>BEV 200–300</td><td>9</td><td rowspan="2">BEV 250</td><td rowspan="2">73</td></tr>
<tr><td>Tesla</td><td>64</td></tr>
</table>

3.2 Daily miles driven

Figure 5 shows the daily driving distance distribution by vehicle groups. Overall, drivers of the PHEVs and Teslas have similar daily mileage distributions with average daily mileage near 25 miles and numerous outliers corresponding to long trips. The distribution of long trips for Tesla and PHEV drivers is similar perhaps because both vehicle types have access to extended range capabilities—Teslas through their long-range and widespread public charging network and PHEVs through their internal combustion engines. All Tesla miles are electric whereas PHEV miles are approximately 60% electric and 40% gasoline powered. Drivers in the BEV200–300 group travel an average of 33 miles per day. Of these nine BEV200–300 drivers, six drivers drive an average of 60 or fewer miles per day, while the other three drive an average of 70, 86, and 96 miles per day. The fewest number of average daily miles is traveled by the BEV100–200 group who travel an average of 12 miles per day. In average, all vehicle considered, 20.4 miles are driven daily in electric mode, which corresponds to an annual mileage of 7,446 electric miles.

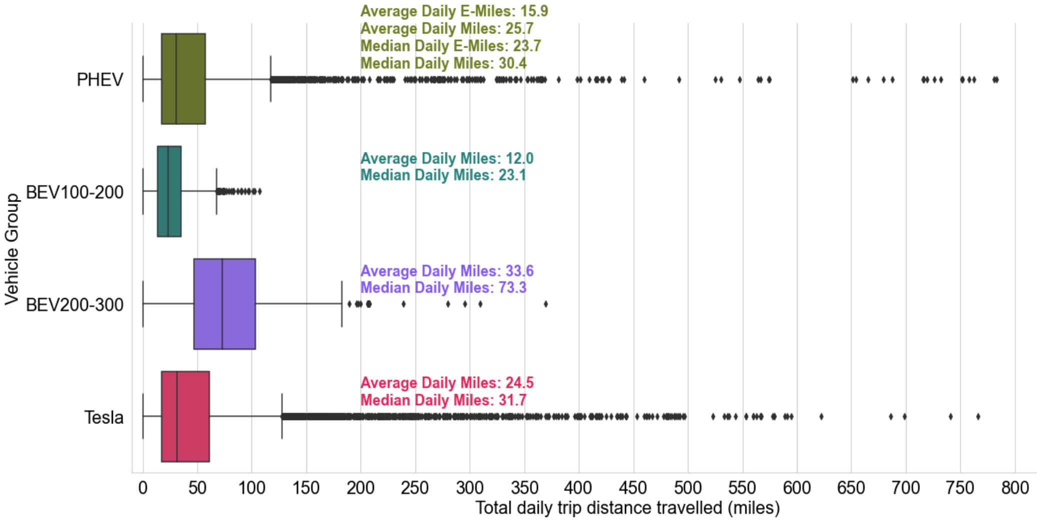

Figure 5: Distribution of daily driving distance (miles) by vehicle group

3.3 Home charging capabilities

Table 4 shows how the charge rates (kW) are associated with each vehicle group. Note that there are two instances of Tesla drivers owning two separate Teslas in the study. In addition, one PHEV household also owns a Tesla, which is why there is a high L2 charge associated with the group. With two long-range BEVs in one household, there will be a tendency to have higher power charging to be able to charge both vehicles easily at home.

Table 4: Number of home chargers at each power level in the Southern data

	PHEV	BEV100–200	BEV200–300	Tesla
L1 (0–2 kW)	14 [36%]	7 [39%]	2 [25%]	1 [2%]
Low L2 (2–8 kW)	24 [61%]	11 [61%]	6 [75%]	9 [16%]
High L2 (8–20 kW)	1 [3%]	-	-	46 [82%]

For simplicity, in the EV load profile tool, L1, low L2, and high L2 are associated with a power capability of 1.44, 6.6, and 11 kW, respectively. Table 5 shows the home charging probabilities for the EV load profile tool. It is important to note that the normalized value is more important for the tool than the absolute value.

Table 5: Number of home chargers at each power level for the load profile tool

	PHEV40	BEV150	BEV250
L1 (1.44 kW)	14 [36%]	7 [39%]	3 [4%]
Low L2 (6.6 kW)	24 [61%]	11 [61%]	15 [24%]
High L2 (11 kW)	1 [3%]	-	46 [72%]

3.4 Energy efficiency

Figure 6 shows the average energy efficiency (miles per kWh) for each vehicle group of the Southern data by month. The error bands are calculated based on the range of energy efficiencies for each vehicle group, while the line is the average. Vehicle energy consumption is highly dependent on the ambient outdoor temperature, which influences drivers to cool or heat the vehicle cabin. Consequently, the heating and cooling loads impact the overall vehicle energy consumption. In the load profile tool, for simplicity, an average value of energy efficiency for each EV type has been chosen based on data displayed in Figure 6. The PHEV40, BEV150, and BEV250 types have an average energy efficiency of 2.7, 2.5, and 2.3 mi/kWh, respectively.

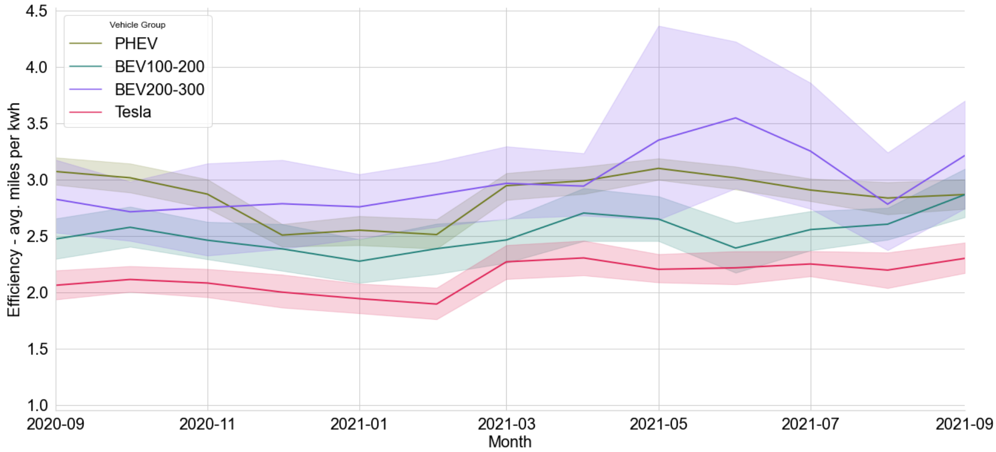

Figure 6: Average efficiency for each vehicle group of the Southern data

3.5 TOU participation

Alabama Power has a rate rider for EVs that encourages home charging during the off-peak time from 9 pm to 5 am any day of the year through reduced rates during that time period. Table 6 illustrates the distribution of the 135 drivers: 95 (70%) are on Alabama Power's EV rate rider, 19 (14%) are not, and 21 (16%) did not provide TOU information. Therefore, for the EV load profile tool, it is considered that 70% of the population is enrolled in the TOU plan and 30% is not. Survey data indicate that most drivers who are enrolled in the rate rider configure their EVs or their home chargers to start charging after 9 pm. However, some drivers opt to program their EVs to be fully charged by the morning (5 am), and some drivers manually plug in their cars after 9 pm.

Table 6: TOU plan statistics of the Southern Company data

	Drivers on TOU	Drivers Not on TOU	Unknown TOU Status
PHEV	30 [69.7%]	6 [13.9%]	7 [16.4%]
BEV100–200	14 [73.7%]	3 [15.8%]	2 [10.5%]
BEV200–300	8 [88.8%]	0 [0%]	1 [11.2%]
Tesla	43 [67.2%]	10 [15.6%]	11 [17.2%]

4 Validation of Load Profile Tool

This compares the EV load profile tool outputs against the Southern Company data. First, some of the tool parameters need to be adjusted. Based on the Southern Company data, many parameters are given, such as the size of the population (cf. Table 3), the number of EV drivers enrolled in a TOU plan (cf. Table 6), or the probability to access a L1, a low L2, or a high L2 charger when the electric car is recharged at home (cf. Table 5). However, the data do not show the probability that a driver will park their EV at home or at any other location (for example, at work or in a public place) without plugging it in—parameters that the load profile tool requires. Such values are found by a trial and error process and are presented in Table 7. The location "Mid-trip" corresponds to the need for a BEV to stop at a DC fast charging station during a long trip. “Public” represents all the charging locations outside the home and workplace and is not related to DCFC during a long trip. The “0 kW” column is the probability of not recharging when an EV is parked.

The ratio for home charging (0 kW excluded) is the same as the probabilities described in Table 5. Furthermore, according to Figure 5, it is considered that only BEV250 go on long trips and therefore can recharge during mid-trip. It is assumed that only low L2 chargers are available at “work.” For “public” locations, PHEV and BEV150 are limited to low L2 chargers, whereas BEV250 can access faster recharge solutions. The EV load profile tool assumes that a real driver would plan ahead and use a conventional or hybrid vehicle to complete any series of trips away from home that could not be driven from start to finish in their BEV due to insufficient charging infrastructure. Therefore, any series of trips deemed unachievable by the tool would be removed entirely—through the “trip-chain” rule feature—that is, the energy needed to complete it would be simulated as being powered by conventional means and so would not require replenishing from the grid.

Table 7: EV load profile tool charging probabilities

Location	Vehicle Type	0 kW	1.44 kW	6.6 kW	11 kW	50 kW	150 kW
Home	PHEV40	0.31	0.2484	0.4209	0.0207	0	0
	BEV150	0.815	0.07215	0.11285	0	0	0
	BEV250	0.35	0.026	0.156	0.468	0	0
Work	PHEV40	0.77	0	0.23	0	0	0
	BEV150	0.984	0	0.016	0	0	0
	BEV250	0.73	0	0.27	0	0	0
Public	PHEV40	0.94	0	0.06	0	0	0
	BEV150	0.984	0	0.016	0	0	0
	BEV250	0.9	0	0.03	0.03	0.02	0.02
Mid-trip	PHEV40	1	0	0	0	0	0
	BEV150	1	0	0	0	0	0
	BEV250	0	0	0	0	0.5	0.5

Correct charging probabilities are found when the annual mileage and the energy consumption by location for each vehicle type—provided in Table 8 and Figure 7, respectively—produced by the EV load profile tool match those obtained during the Southern Company study. According to Table 8 and Figure 7, the choice of charging probabilities in Table 7 is accurate. Indeed, the annual mileage from the EV load profile tool deviates by less than 1% for any vehicle type compared to the one found in the Southern Company study (cf. Table 8). Moreover, Figure 7 shows that the energy consumption at home for each vehicle type matches perfectly between the Southern Company data and the EV load profile tool. There is always less than 1% difference. Because the “unknown” locations represent a significant portion of the “non-home” energy consumption, the energy consumption at work and public space is more related to an expert guess. Consequently, only the 24-hour EV load shape at home is compared to the Southern Company data.

Table 8: Annual mileage for the Southern Company data and EV load simulation

<table>
<tr><th colspan="3">Southern Data</th><th colspan="2">EV Load Profile Simulation</th></tr>
<tr><th>Vehicle type</th><th colspan="2">Annual mileage</th><th>Vehicle type</th><th>Annual mileage</th></tr>
<tr><td>PHEV</td><td colspan="2">9,380/5,830 elec</td><td>PHEV40</td><td>9,380/5,848 elec</td></tr>
<tr><td>BEV100–200</td><td colspan="2">4,380</td><td>BEV150</td><td>4,378</td></tr>
<tr><td>BEV200–300</td><td>12,264</td><td rowspan="2">9,344</td><td rowspan="2">BEV250</td><td rowspan="2">9,380</td></tr>
<tr><td>Tesla</td><td>8,979</td></tr>
</table>

Retrospectively, it can be noted that the annual mileage and charging probabilities for PHEV40 and BEV250 are similar. The main difference between the two is related to the access to a DCFC station. The BEV150 annual mileage and charging probabilities are set up differently: They rarely recharge in public places, at work, or at DCFC locations although the infrastructure is available to them (that is, PHEV and BEV250 do recharge more often there). Moreover, BEV150 owners drive half as much as the PHEV and BEV250. Perhaps those owners within Southern Company bought those EVs with the intent to recharge at home and only drive a daily commute.

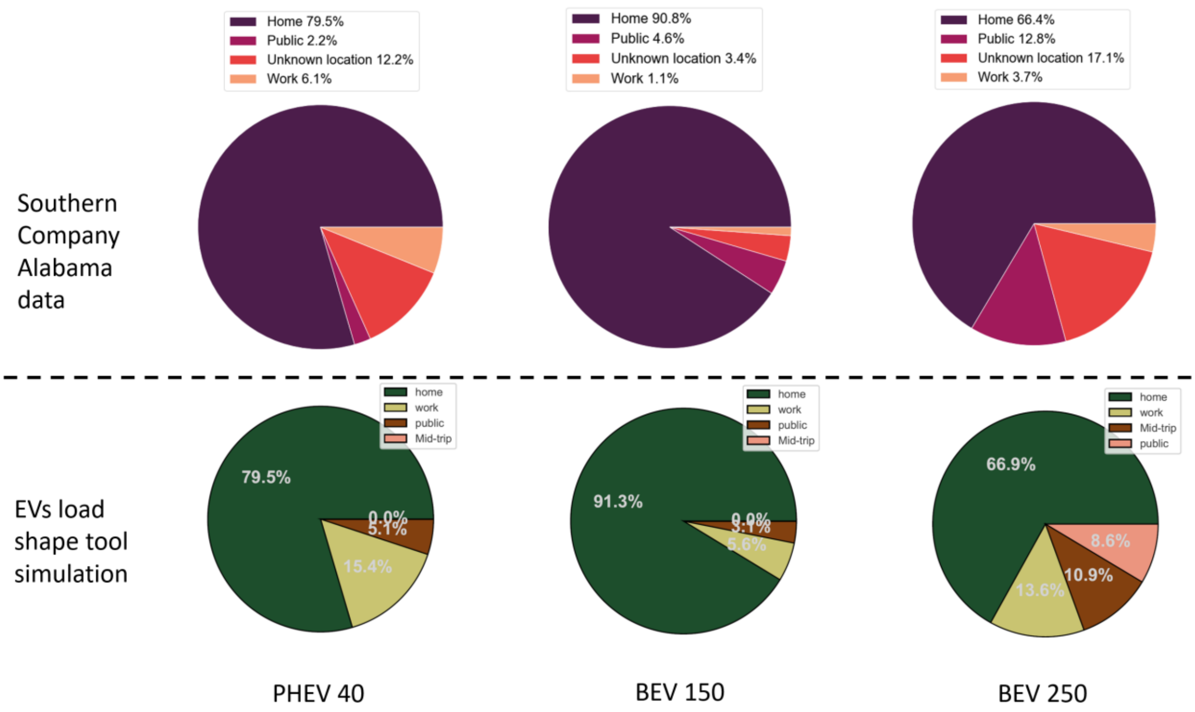

Figure 7: Energy consumption by location for each vehicle type by percentage of recharged kWh

Figure 8.a to 8.d provides the 24-hour load shape per vehicle for the 135 studied vehicles (Figure 8.a) and for each EV type (PHEV40: Figure 8.b; BEV150: Figure 8.c; BEV250: Figure 8.d). Overall, the EV load profile tool provides accurate estimation of the magnitude and shape for the entire population and each EV type:

- The power peaks soon after the beginning of the off-peak period (9 pm to 5 am).
- The power declines slowly from midnight to 5 am.
- The power is low and increases slightly during the on-peak period (5 am to 9 pm).

Moreover, the simulated peak load values are always within the margin of error of measured data. The main visible difference between the simulated load shape and the Southern Company data appears during early morning BEV150 load shape. Such difference can easily be explained by the low number of miles driven by BEV150 drivers. Indeed, they typically drive 50% less than gasoline engine drivers. Moreover, BEV150 drivers never go on a trip longer than their BEV range as shown in Figure 5. Because the computation is based on NHTS data, which describe the typical behavior of a conventional car driver, many NHTS trips are deemed unfeasible and therefore removed from the EV load shape for BEV150. However, the load profile tool can accurately capture the charge schedule of the BEV250. Numerous data show that the vast majority of projected EVs are BEV250 [14, 15]; therefore, the inability of the tool to properly describe the charge behavior of BEV150 is a minor issue. Even in this study, the load profile tool provides accurate results for the 135 studied vehicles (cf Figure 8.a) despite the difficulty in precisely capturing BEV150 charge behavior because the BEV150 represents only 19 vehicles of the 135 studied—and the BEV150 load shape peak amplitude is about half (0.6 kW vs. 1.2 kW) of the BEV250.

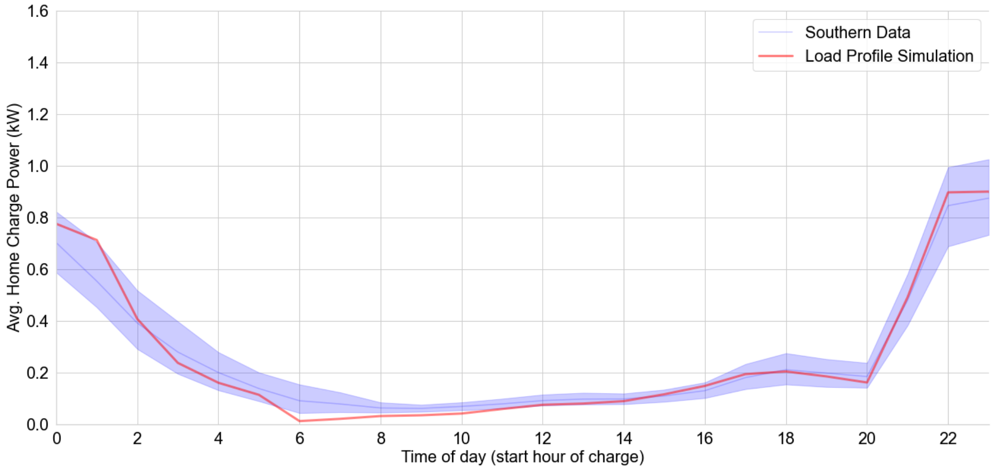

Figure 8.a: 24h load profile per vehicle for the 135 studied vehicles

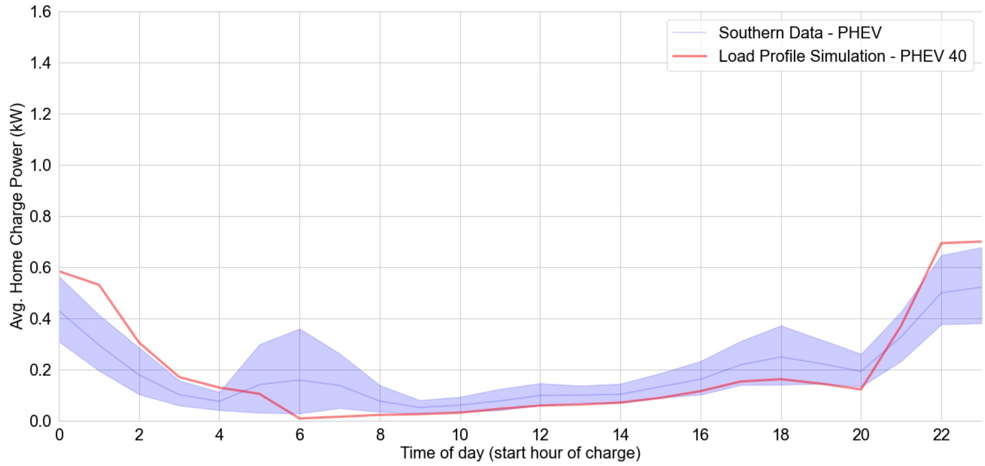

Figure 8.b: 24h load profile per vehicle for PHEV40 group

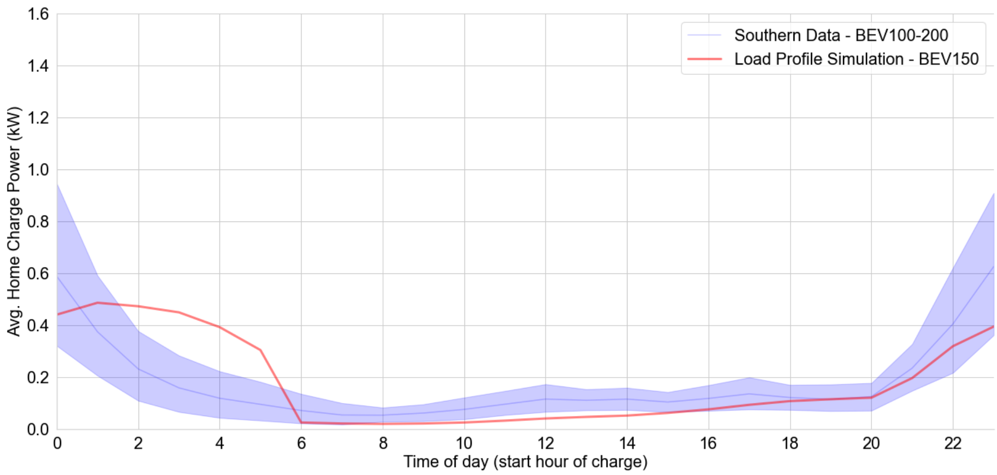

Figure 8.c: 24h load profile per vehicle for the BEV150

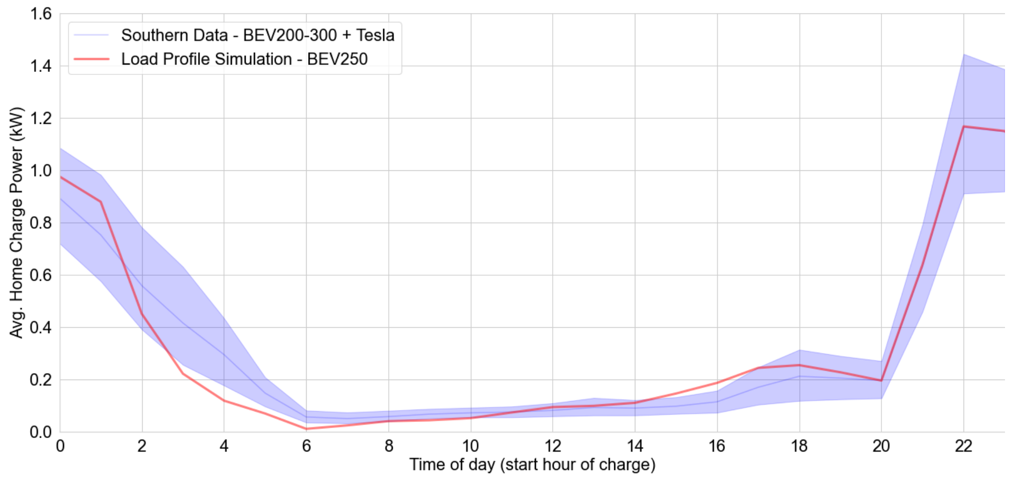

Figure 8.d: 24h load profile per vehicle for the BEV250

5 Conclusions

This paper describes a new EV load profile profile tool developed by EPRI. It is meant to estimate current and future grid energy needs for charging a population of EVs. The tool is designed to help utilities accurately plan what future generation resources will be needed to provide the forecasted energy demand from new EVs as well as evaluate different strategies, such as TOU rates or charge demand management, that can incentivize EV drivers to shift their charging behavior.

Through this paper, the EV load profile tool output is compared to real data collected by Southern Company through a joint study with EPRI. This study aims to understand EV charging behavior and ensuing load shapes by analyzing the EV charging and driving behavior of 135 participants in Alabama across an entire year.

This validation process leads to two main conclusions. First, the EV load profile tool can provide realistic and insightful information concerning load shape and magnitude. Therefore, its utilization to forecast future EV charging load is a major advantage that utilities can leverage to make informed decisions and plan the future grid infrastructure and resources. Second, the tool is highly sensitive to the parameters used for the simulation. In fact, the most important part of the work consists of determining the correct parameters. While comparing the EV load profile tool output to the Southern Company data, the task was moderately complex because the Southern Company data provided most of the required parameters. However, in a future project where a utility company requests EV load profiles for a specific region, additional assumptions about the simulation parameters will be required.Determining them realistically is the main challenge when it comes to forecasting the relevant EV load shape.

Further validation of the EV load profile tool can be executed, with a larger population, in a different area of the country where people's behavior, fleet and infrastructure advancement status, and climate conditions are different. There are many potential use cases for the EV load profile tool; for instance, it can help project how TOU rates can impact load shape. In the context of shifting load to different hours of the day, this tool can be used to evaluate how much energy can be shifted from on-peak to off-peak times, which can help to flatten the "duck curve." [16, 17] Moreover, this tool can be used for evaluating the new load that represents the electrification of medium- and heavy-duty vehicles.

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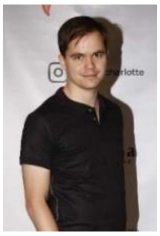
Presenter Biography



Nicolas Sockeel completed his PhD in electrical and computer engineering at Mississippi State University in 2018. He received his Bachelor (2013) and Master of Engineering (2015) at EPF Graduate School of Engineering, France.

Currently, he is an Engineer/Scientist III at the Electric Power Research Institute (EPRI). Nicolas works in EPRI’s Charlotte office with the Electric Transportation team. His main focus is the EV load shape tool.