


## Article

# Reliability-as-a-Service Usage of Electric Vehicles: Suitability Analysis for Different Types of Buildings

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**Abstract:** The use of electric vehicles (EVs) to provide different grid services is becoming possible due to the increased penetration levels, mileage efficiencies, and useable battery sizes of EVs. One such application is providing reliability-as-a-service (RaaS) during short-term power outages. Instead of using a dedicated backup power source, EVs can be contracted to provide RaaS, which is an environmentally friendly solution with benefits for both building owners and EV owners. However, the presence of EVs at a particular location during different hours of the day and the availability of energy from EVs is uncertain. Therefore, in this study, a suitability analysis is performed concerning the use of EVs to provide RaaS for different types of buildings. First, the National Household Travel Survey (NHTS) survey data are used to estimate driver behavior, such as arrival/departure times, daily mileage, and traveling duration. Then, the usable battery size and mileage efficiency of EVs is extracted from the database of commercially available EVs. Based on these parameters, the daily energy consumption and available energy of EVs to provide RaaS are estimated. A suitability analysis is conducted for residential, commercial/industrial, and mixed buildings for both weekdays and holidays. The participation ratio of EV owners is varied between 10 and 90%, and nine cases are simulated for commercial/industrial buildings and multi-unit residential buildings. Similarly, the ratio of home-based EVs is varied between 5 and 50%, and 10 cases are tested for mixed buildings. The analysis shows that mixed buildings are the most suitable, while commercial/industrial buildings are the least suitable for using EVs to provide RaaS. To this end, an index is proposed to analyze and determine the desired ratio of EVs to be contracted from homes and workplaces for mixed buildings. Finally, the impact of EV fleet size on the available energy for RaaS is also analyzed.

**Keywords:** backup power; electric vehicle; home and workplace; power outage; reliability-as-a-service; suitability analysis; vehicle-to-grid



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## 1. Introduction

A continuous supply of electricity is required in all sectors not only to run daily routine activities but also to keep critical services functional during loss of connection with the grid. Loss of connection could be due to either reliability-oriented events or resilience-oriented events. The former refers to small-scale outages with a typical duration of minutes to hours, while the latter refers to large-scale outages with a typical duration of hours to days [1]. In the case of resilience-oriented events, residents may need to evacuate, and other infrastructure may also be compromised. During reliability events, there is no emergency except temporary loss of connection to the grid due to the failure of a line or a generation unit [2]. Therefore, backup generators are generally used in buildings, especially multi-unit buildings, to keep the required services running during power-outage periods. The use of backup power resources is common both in the residential and commercial sectors [3]. Diesel generators are the most commonly used backup generators due to their relatively lower initial costs and higher energy density [4]. However, diesel generators are not environmentally friendly and require proper maintenance throughout the year [5].

Recently, the battery energy storage system (BESS) has been considered as an alternative green option to serve as a backup power source [6]. However, the upfront cost of BESS is higher, and the frequency of outage events is low, i.e., about nine hours per year [7]. BESS needs to be installed and maintained throughout the year to prepare for such events. This results in increased costs for building owners/operators. Meanwhile, the penetration of electric vehicles (EVs) is increasing in the transport sector, and the global EV fleet is projected to reach between 140 and 245 million by 2030 [8]. In addition, the useable battery size and energy consumption efficiency of EVs are also increasing [9]. This provides opportunities for using EVs to provide reliability-as-a-service (RaaS) during reliability-oriented events. The use of EVs to provide RaaS could be especially beneficial for multi-unit residential buildings or commercial/industrial buildings where several cars are parked together in a shared parking location.

The use of EVs to provide RaaS will be beneficial for both building and EV owners. It will reduce investment and operation costs for building owners while creating additional revenues for EV owners. Several studies have been conducted on the use of EVs to provide different services to power grids, such as peak shaving [10], frequency regulation [11], and voltage control [12]. The economic benefits of different vehicle-to-grid (V2G) services are analyzed in [13], and the benefits of V2G services in renewable-coupled systems are analyzed in [14]. However, these services are required on daily basis in power systems, and EVs need to be called frequently. This could increase battery degradation, which is considered one of the main obstacles in registering for any V2G program [15]. However, due to the lower frequency of reliability events, RaaS usage of EVs can be considered a practical solution. In addition, EV owners can contract for the amount of energy they can provide per year/event based on their daily mileage and the desired minimum state-of-charge (SoC) level in the EV.

To assess the economic feasibility of using EVs to provide RaaS, the authors conducted an initial study [16]. A reward mechanism is proposed to provide incentives to EV owners to register and comply with their RaaS contracts. In addition, yearly revenue for EV owners is estimated under extreme cases, i.e., no events and one event per month. Results have shown that using EVs can reduce costs for building operators as compared to diesel generators and BESS, while generating additional revenue for EV owners. However, there are several uncertainties associated with EVs compared to dedicated backup resources (diesel generators and BESS), which are as follows:

- The presence of EVs in a particular location during different hours of the day varies, leading to uncertainty.
- The amount of energy available from each EV to provide RaaS during any event is uncertain.
- The probability of the presence of EVs in a particular location could be different for weekdays and holidays, especially for workplaces.
- The percentage of EV owners willing to participate in the RaaS program could also vary from location to location.

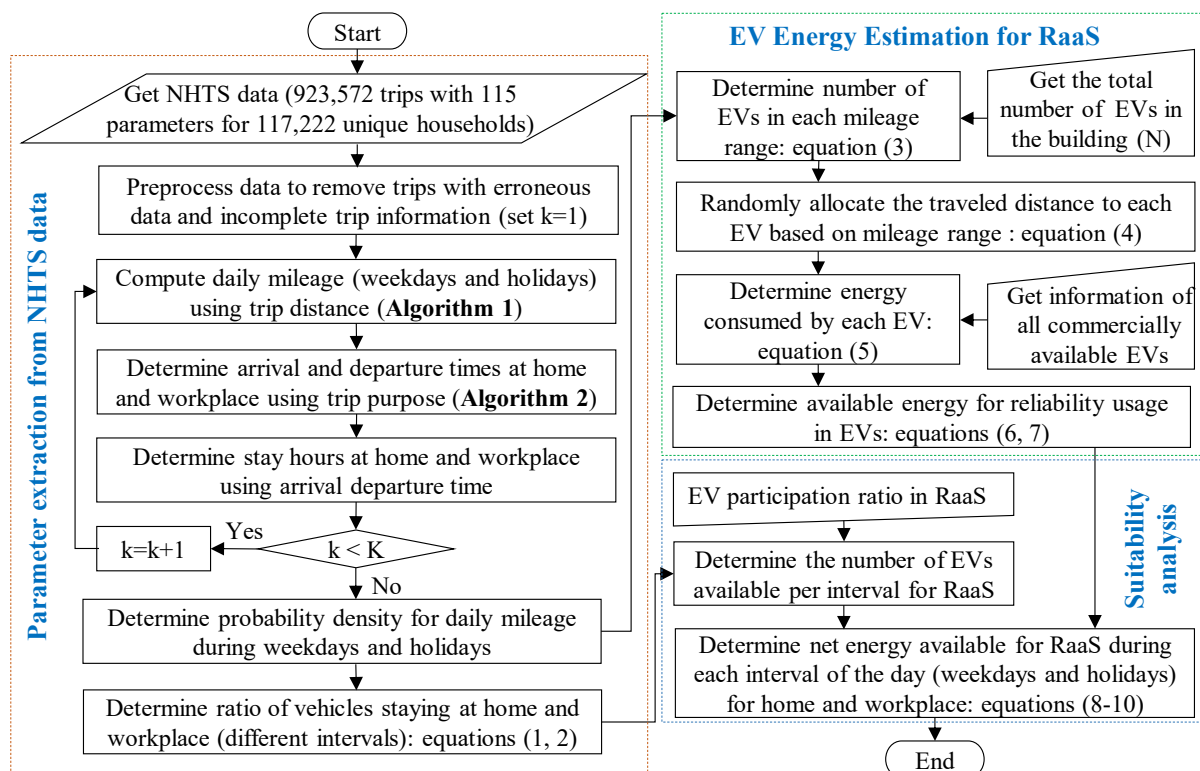
Therefore, a stochastic analysis is required to determine the potential of using EVs to provide RaaS. Several factors, such as EV parameters (battery size, mileage efficiency, and SoC), EV driver behavior (daily mileage, arrival and departure times, required energy for upcoming trips, etc.), building types (residential, commercial/industrial, and mixed), and day types (working days and holidays) must be considered. This information can be used to determine the suitability of RaaS usage of EVs for different building types. In addition, the number of EVs required to provide a certain amount of energy for different types of days should also be determined.

Based on the insights gained from the economic feasibility analysis [16], the suitability analysis concerning the use of EVs to provide RaaS is carried out in this study. To capture the stochastic behavior of vehicle owners, the U.S. National Household Travel Survey (NHTS) dataset [17] is used, and different parameters are estimated. These parameters include home/workplace arrival/departure times, daily mileage of vehicles, and duration

of trips. In addition, the parameters of EVs are extracted from the database of commercially available EVs [18] to date. These parameters include the useable battery size and the energy consumption efficiency of EVs. Then, a suitability analysis concerning the use of EVs to provide RaaS for residential, commercial/industrial, and mixed buildings with shared parking spaces is carried out. The analysis is conducted for both weekdays and holidays. An index is also proposed to analyze the variations in the available energy of EVs for RaaS at different hours of the day. Then, the desired ratio of EVs to be contacted from homes and workplaces is determined for mixed buildings. The objective of this index is to minimize the variation in available energy to be used simultaneously as backup power for both weekdays and holidays.

## 2. Parameter Extraction from NHTS Data

To estimate the amount of energy available in EVs to provide RaaS for different buildings, two types of data are required. The first category of data is related to the behavior of vehicle drivers, and the second category is related to EVs. In this section, data related to vehicle drivers are discussed. These data include the daily mileage of vehicles, the arrival/departure time of vehicles at home/workplace, and the stay hours at home/workplace. These are stochastic parameters, and a large and reliable dataset is required due to differences in the social dynamics and personal preferences of vehicle drivers [19]. Such a dataset is not yet available for EVs. Therefore, the NHTS dataset [17] is used in this study to extract these parameters, as shown in Figure 1. The survey dataset contains 923,572 trip datapoints for 117,222 households with 203,007 vehicles. This dataset is considered reliable, and it has been used by several researchers for EV load estimation [20,21]. The extracted data are then translated into EVs, which will be discussed in the next section.



**Figure 1.** Flowchart for parameter extraction and suitability analysis of RaaS usage of EVs.

The step-by-step process of data extraction, EV energy estimation for proving RaaS, and suitability analysis for different building types is shown in Figure 1. This section deals with extraction of NHTS data, while the remaining two parts will be discussed in the subsequent

sections. It is worth noting that the NHTS survey data constitute a raw dataset, which needs to be filtered first to remove erroneous entries and trips with incomplete information.

### 2.1. Data Preprocessing

The first step is to preprocess the NHTS data to remove trips with erroneous, unrealistic, and unreported data. The NHTS data provide 115 parameters per trip; details about these parameters can be found in [22]. In this study, filters are applied for only parameters of interest for this study. Some examples of filters used in this study are as follows.

- Remove trips with unreported trip mileage and/or unreported trip duration.
- Select only trips with driving mode as car, SUV, minivan, and pickup truck (remove trips on motorcycle, bicycle, school bus, public or commute bus, etc.).
- Remove trips with unidentified vehicle ID.
- Remove trips with an unspecified origin/destination and day of the trip.
- Calculate vehicle speed using reported mileage and trip duration, then remove trips with unrealistic speeds.

After applying these filters, the number of trips is reduced to 788,613 for 110,272 households with 137,382 unique vehicles. These data are used for further analysis in this study. It is worth mentioning that in this study, vehicles are tracked instead of people since one person could use different vehicles for different trips, and multiple residents of a household could use a single vehicle.

### 2.2. Daily Mileage of Vehicles

The overall process for the daily mileage computation is shown in Algorithm 1. First, the mileage of all vehicles during weekdays ( $D_i^{wd}$ ) and holidays ( $D_i^{hd}$ ) is initialized to zero. Then, the trip counter ( $k$ ) and vehicle counter ( $i$ ) are initialized, as shown in line 2. Then, unique vehicles are identified using vehicle ID ( $V_k^{id}$ ) and household ID ( $HH_k^{id}$ ) fields of NHTS data, lines 3–6. After identifying a unique vehicle ( $i$ ), all trips ( $k$ ) covered by that vehicle are tracked, and the distance covered in each trip ( $D_k$ ) is extracted from the covered-mileage field of NHTS data. Two separate variables are maintained to store the daily mileage of vehicles during weekdays ( $D_i^{wd}$ ) and holidays ( $D_i^{hd}$ ), lines 7–11. This process (lines 3–13) is repeated until all reported trips are scanned.

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#### Algorithm 1 Daily mileage computation for vehicles.

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1: Initialize mileage of weekdays ( $D_i^{wd} = 0, \forall i \in I$ ) and holidays ( $D_i^{hd} = 0, \forall i \in I$ )
   for each vehicle
2: Initialize trip counter  $k = K$  (total trips in filtered data) and vehicle counter  $i = 0$ 
3: while ( $k > 0$ ) do
4:   if ( $V_k^{id} \neq V_{k-1}^{id}$  or  $HH_k^{id} \neq HH_{k-1}^{id}$ ) do // Tracking unique EVs
5:     |    $i = i + 1$ 
6:   end if
7:   if (Trip Day  $\in$  Weekdays) do
8:     |    $D_i^{wd} = D_i^{wd} + D_k$ 
9:   else
10:    |    $D_i^{hd} = D_i^{hd} + D_k$ 
11:   end if
12:    $k = k - 1$ 
13: end while

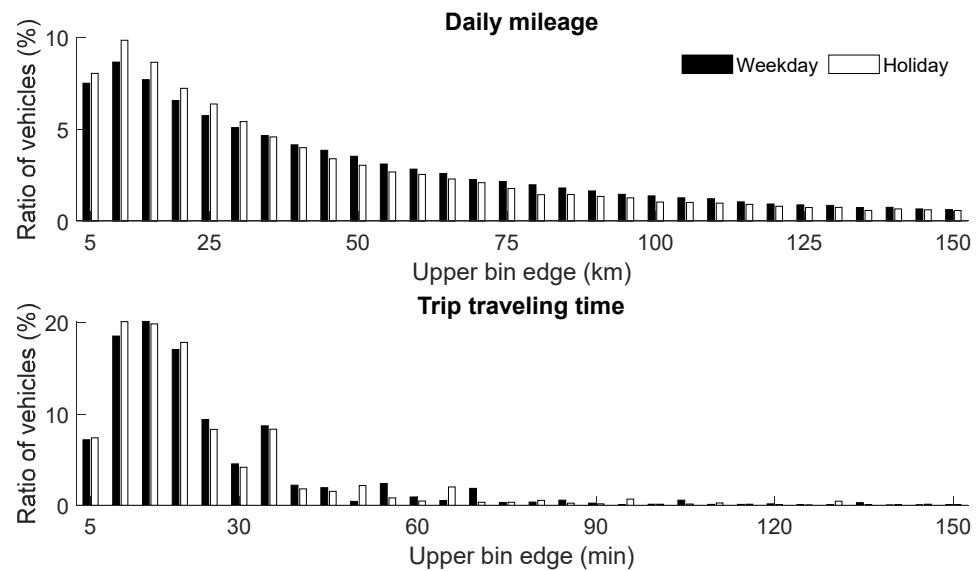
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The results obtained for the daily mileage of vehicles during weekdays and holidays are shown in Figure 2. For the sake of visualization, data beyond 150 km is clipped in the figure. The histogram shows that the daily mileage follows a lognormal distribution, and the majority of vehicles travel less than 100 km a day. The overall histogram pattern is similar for both weekdays and holidays, with minute differences in some bin edges.



These daily mileage data are later used to compute the amount of energy consumed by EVs to carry out their daily activities or to allocate energy for upcoming trips. Similarly, the travel duration of each trip is shown in the bottom part of Figure 2 for both weekdays and holidays. It can be observed that most of the trips last for less than an hour, with a higher concentration in the region of under 30 min.



**Figure 2.** Daily mileage and per-trip travelling-duration histograms for vehicles.

### 2.3. Daily Arrival and Departure Times

The next step is to track the arrival and departure times of vehicles at/from home and the workplace. The overall process for tracking arrival and departure times of vehicles is shown in Algorithm 2. First, home arrival ( $T_i^{hax}$ ) and departure ( $T_i^{hdx}$ ) times for weekdays/holidays are initialized to zero for all vehicles. Then, workplace arrival ( $T_i^{wax}$ ) and departure ( $T_i^{wdx}$ ) times for weekdays/holidays are initialized to zero. Then, the trip counter ( $k$ ) and vehicle counter ( $i$ ) are initialized, as shown in line 3. Similarly to daily mileage tracking, unique vehicles are identified first, lines 5–7. The trip day field is tracked to identify weekdays and holidays for each vehicle trip, line 8. For each working day, the trip departure-point field is tracked to identify home and workplace, lines 9, 10. The trip departure time for trip  $k$  ( $T_k^{dep}$ ) is set to home departure time ( $T_i^{hdw}$ ) if the trip originated from home, and it is set to the workplace ( $T_i^{wdw}$ ) if it originated from the workplace. Similarly, the arrival time for each trip is tracked based on the destination point of the trip, lines 12–14. If the trip is destined for home, trip arrival time ( $T_k^{arr}$ ) is set to home arrival time ( $T_i^{haw}$ ), and it is set to workplace arrival time ( $T_i^{waw}$ ) if it was destined for the workplace. The same process is repeated for holidays, and the corresponding parameters are extracted, lines 16,17. It should be noted that the last arrival time is recorded for home, while the first arrival time is recorded for workplace arrival, i.e., in-between short trips are ignored.

The obtained results for daily arrival and departure times of vehicles during working days and holidays are shown in Figure 3. As expected, sharp peaks are observed for weekdays, while more flattened curves are observed for holidays. All these results are self-normalized; therefore, arrival and departure time curves for the workplace during holidays can also be seen. However, the number of vehicles is significantly lower for holidays as compared to weekdays, which is discussed in the following subsection. Figure 4 shows the cumulative densities for arrival and departure times for home (HO) and workplace (WP) during working days and holidays. Sharp rises in the cumulative density plots can be

observed for weekdays (peak arrival and departure hours), while monotonically increasing plots can be observed for holidays.

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**Algorithm 2** Arrival and departure times tracking of vehicles.

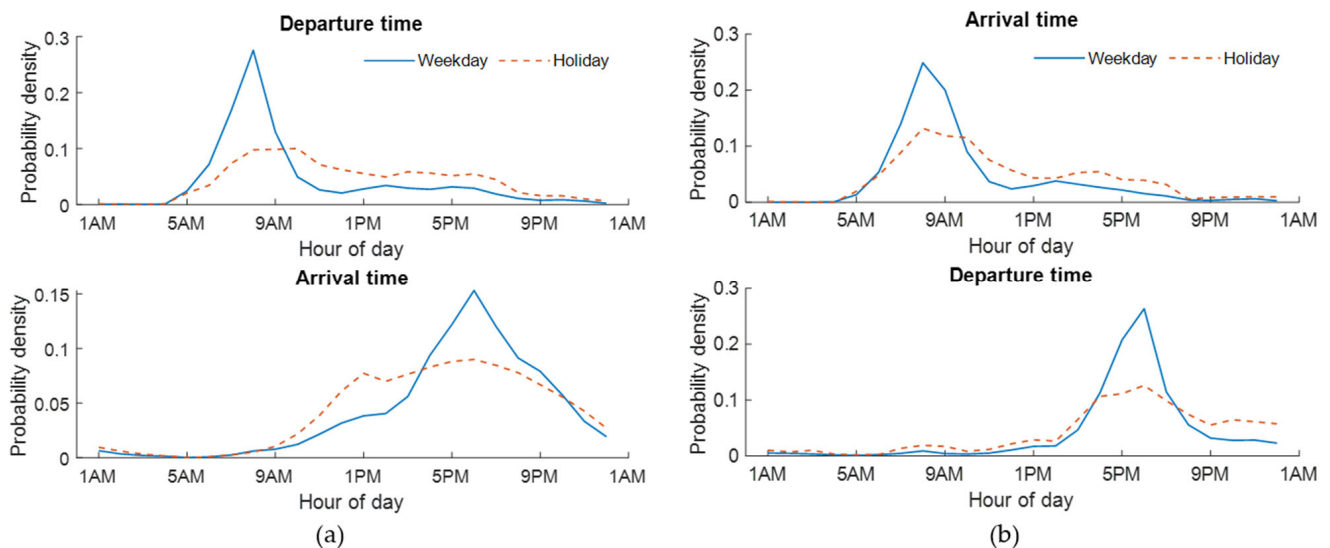
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1: Initialize home arrival/departure time for weekdays/holidays ( $T_i^{hax}, T_i^{hdax} = 0, \forall i \in I$ )
2: Initialize workplace arrival/departure time for weekdays/holidays
   ( $T_i^{wax}, T_i^{wdax} = 0, \forall i \in I$ )
3: Initialize trip counter  $k = K$  (total trips in filtered data) and vehicle counter  $i = 0$ 
4: while ( $k > 0$ ) do
5:   if ( $V_k^{id} \neq V_{k-1}^{id}$  or  $HH_k^{id} \neq HH_{k-1}^{id}$ ) do // Tracking unique EVs
6:      $i = i + 1$ 
7:   end if
8:   if (Trip Day  $\in$  Weekdays) do
9:     If (Trip Departure Point is Home):  $T_i^{hdw} = T_k^{dep}$ 
10:    else if (Trip Departure Point is Workplace):  $T_i^{wdw} = T_k^{dep}$ 
11:    else:  $T_i^{hdw} = T_i^{wdw} = -1$ 
12:    If (Trip Arrival Point is Home):  $T_i^{haw} = T_k^{arr}$ 
13:    else if (Trip Arrival Point is Workplace):
14:      If (First Arrival):  $T_i^{waw} = T_k^{arr}$ 
15:      else:  $T_i^{haw} = T_i^{waw} = -1$ 
16:    else
17:      Repeat steps 8–14 for holidays and store data in  $T_i^{hdh}, T_i^{wdh}, T_i^{hah}, T_i^{wah}$ 
18:    end if
19:     $k = k - 1$ 
20:  end while

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**Figure 3.** Probability densities of arrival and departure times: (a) home; (b) workplace.

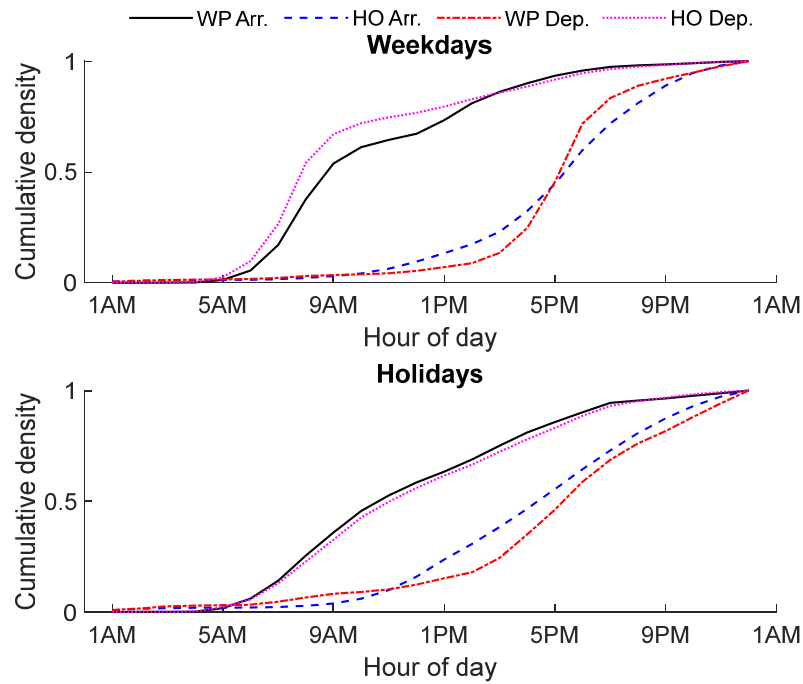


Figure 4. Cumulative densities for arrival/departure time for home/workplace.

#### 2.4. Vehicle Stay Time

The percentage of vehicles staying at home is computed using the accumulated density values of arrival and departure times, shown in Figure 4. In addition, information regarding the ratio of vehicles returning to home ( $R_{ratio}^h$ ) is also required. This value is computed by tracking vehicles departing from home and then returning to home for the whole dataset and is around 96% for both weekdays and holidays. The ratio of vehicles staying at home ( $\Gamma_t^h$ ) can be computed using the following equation:

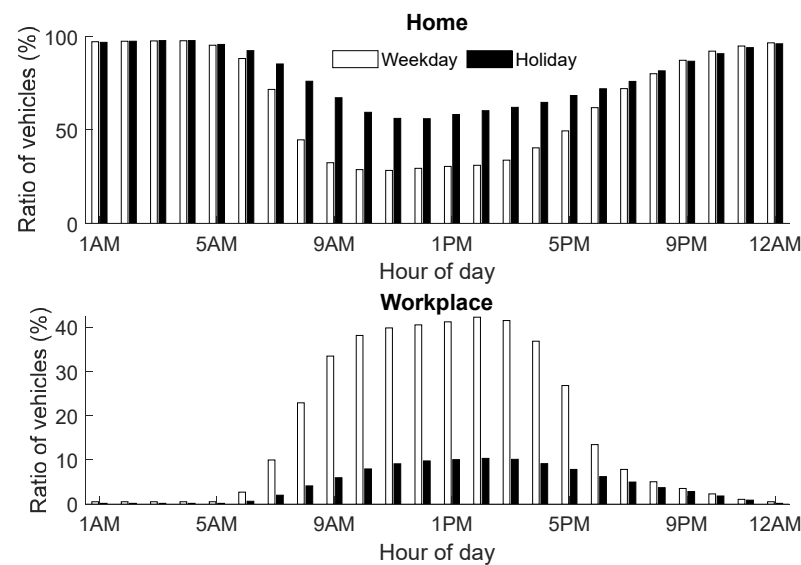
$$\Gamma_t^h = R_{ratio}^h + \sum_{t \in [1,t]} f_t^{ha} - \sum_{t \in [1,t]} f_t^{hd} \quad \forall t \in T \tag{1}$$

where  $f_t^{ha}$  and  $f_t^{hd}$  are the home arrival and departure probability densities, respectively, and summation is used to obtain the cumulative densities. The same process can be repeated for both working days and holidays. Similarly, the percentage of vehicles present at the workplace during different hours of the day ( $\Gamma_t^w$ ) can be computed as follows:

$$\Gamma_t^w = \left( \sum_{t \in [1,t]} f_t^{wa} - \sum_{t \in [1,t]} f_t^{wd} \right) \cdot R_{ratio}^w \quad \forall t \in T \tag{2}$$

where  $f_t^{wa}$  and  $f_t^{wd}$  are the workplace arrival and departure probability densities, respectively, and summation is used to obtain the cumulative densities.  $R_{ratio}^w$  is the ratio of EVs going to work (as compared to the total number of EVs in the sample). The value of this parameter is around 58% for weekdays and 18% for holidays.

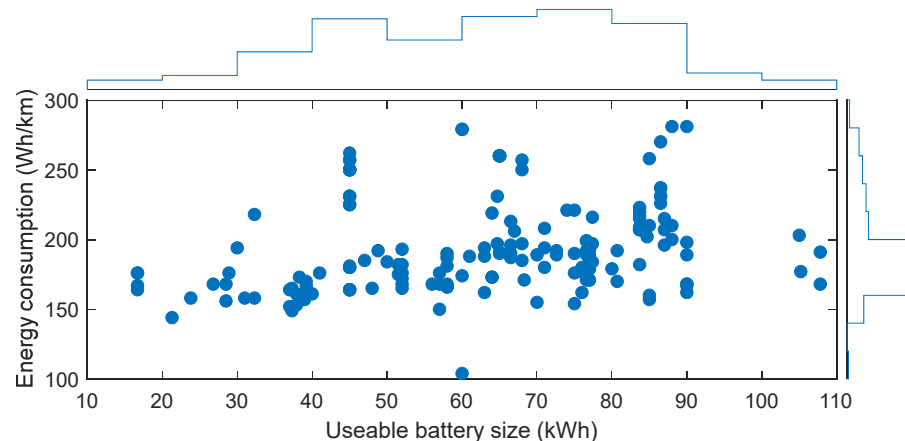
The obtained results are shown in Figure 5. It is evident that most vehicles are present at their home during late-night and early-morning hours, as expected. Similarly, a large portion of vehicles is present at the workplace during working hours. A small fraction of vehicles is present at the workplace during the holidays. This might be due to consideration of Saturdays as holidays, while some industries work Saturdays as well. In addition, some of the essential workforce still works on holidays. These results will be translated into EVs in the following section to determine the available energy of EVs to provide RaaS during different hours of the day.



**Figure 5.** Percent of vehicles staying at home/workplace during different hours of day.

### 3. EV Energy Estimation for RaaS

In this section, the parameters extracted from the NHTS data are applied to EVs, and the available energy in EVs to provide RaaS during different hours of the day is analyzed. First, the useable battery size and energy consumption of all commercially available EVs are taken from [18] and are shown in Figure 6. The average useable battery size of EVs is 58.4 kWh, and the average energy consumption is 195 Wh/km, as of December 2021.



**Figure 6.** Energy consumption and useable battery size of commercially available EVs.

#### 3.1. Allocation of EVs to Different Mileage Ranges

First, the total number of EVs ( $N$ ) is divided into different mileage ranges based on the mileage histogram obtained from the NHTS data, as shown in Figure 2. The number of EVs in each mileage range ( $M_l$ ) can be obtained by using the following equation:

$$M_l = \text{round}(F_l \cdot N) \quad \forall l \in L \quad (3)$$

where  $F_l$  is the histogram value of the daily mileage for bin edge  $l$ . For example, if the total number of EVs is 100, then  $M_1$ ,  $M_2$ ,  $M_3$  and  $M_4$  will be 8, 9, 8, and 7, respectively. This implies that among 100 EVs, eight will travel between 1 and 5 km, nine will travel 5 to 10 km, eight will travel 10 to 15 km, etc. The same process can be repeated for holidays.

Then, the daily mileage of each EV is randomly generated within the range determined using Equation (3). The daily mileage for EVs in any bin edge,  $l$  ( $D_l$ ), is generated using the following equation:

$$D_l = \text{rand}([(l - 1) \cdot b^w, l \cdot b^w], M_l) \quad \forall l \in L \tag{4}$$

where  $b^w$  is the bin width, which is 5 km for weekdays and holidays. It can be observed from (4) that a vector of length ( $M_l$ ) is generated for each bin edge,  $l$ , within the range of  $[(l - 1) \cdot b^w, l \cdot b^w]$ . This process is repeated for holidays to obtain the results for holiday mileages.

### 3.2. Daily Energy Consumption of EVs

After determining the daily mileage of each EV, the energy consumption of each EV is computed using the energy efficiency of commercially available EVs, as shown in Figure 6. Similarly to [23], it is assumed that SoC decreases linearly as a function of the traveled distance, and the energy consumption of EV  $n$  ( $E_n$ ) is computed using the following equation:

$$E_n = (1.60934 \cdot D_n) \cdot \frac{E_n^{pkm}}{1000} \quad \forall n \in N \tag{5}$$

where  $D_n$  is daily mileage in miles, and  $E_n^{pkm}$  is the energy consumption per km in Wh. This process is also repeated for holidays, and obtained results are shown in Figure 7. It can be observed that the daily energy consumption during both weekdays and holidays follows a lognormal distribution (approximated with red curves), similar to daily mileage. It can also be observed from the figures that around 80% of EVs consume under 20 kWh of energy on a daily basis.

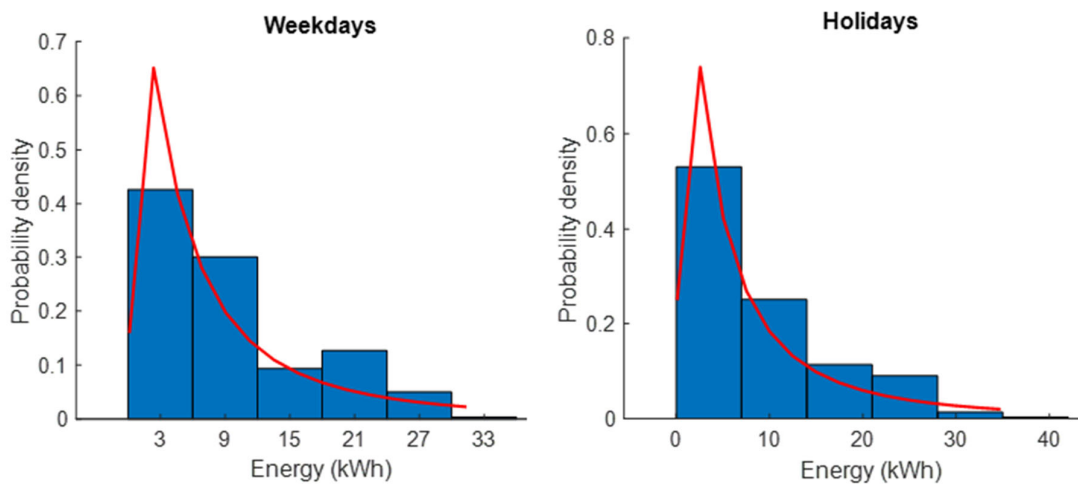


Figure 7. Daily energy consumption of EVs during weekdays and holidays.

### 3.3. Energy for RaaS Usage in EVs

After obtaining the daily mileage and energy consumption of EVs, the energy available in EVs for RaaS can be computed. To calculate the extra energy available in EVs during their stay at home ( $E_n^{ah}$ ), several parameters are required. These parameters include the energy available in the EV at the return time ( $E_n^{rh}$ ), the energy required per day ( $E_n$ ), and preferred minimum level of SoC ( $SoC_n^{\min}$ ), as given by the following equation:

$$E_n^{ah} = E_n^{rh} - E_n - SoC_n^{\min} \cdot B_n^{cap} \quad \forall n \in N \tag{6}$$

where  $B_n^{cap}$  is the capacity of the EV battery in kWh. The energy at the return time is randomly generated in the range of [50%, 80%] of SoC for each EV. The same equation

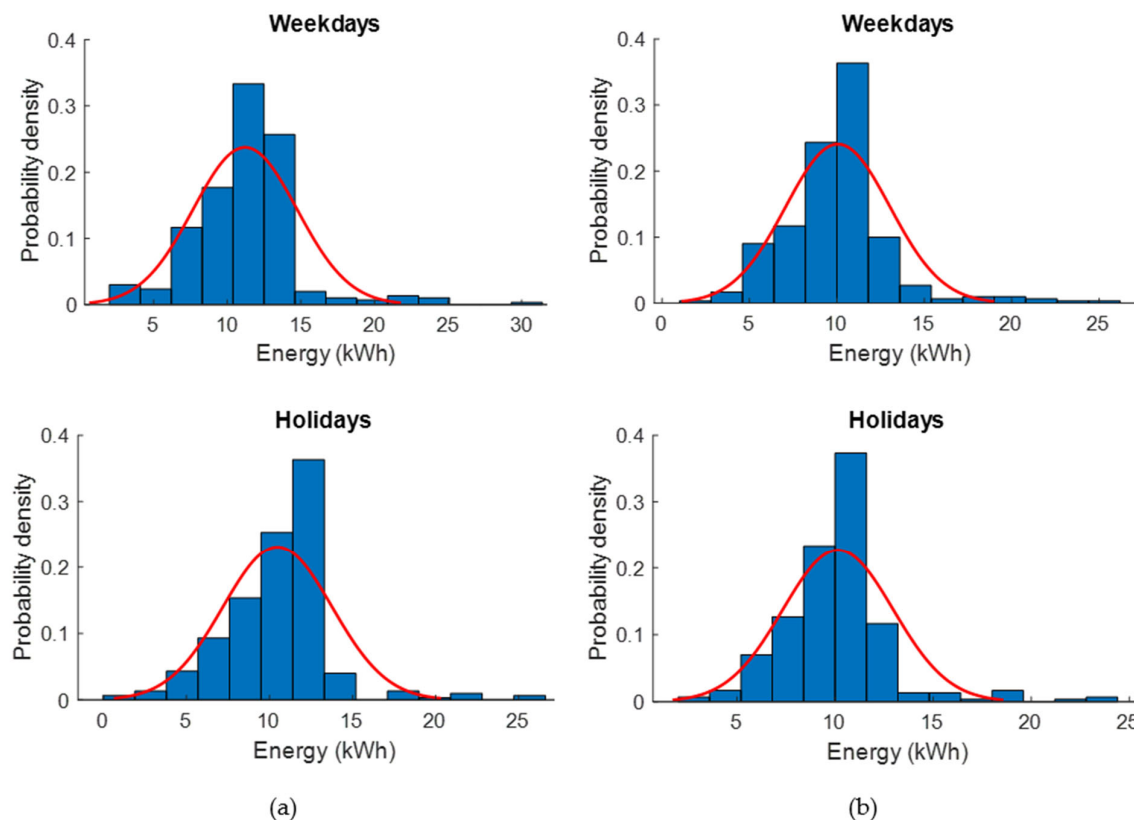


can be used for weekdays and holidays to determine the available energy. Similarly, the following equation can be used to compute the available energy in EVs at the workplace.

$$E_n^{aw} = E_n^{rw} - \alpha_n \cdot E_n - SoC_n^{\min} \cdot B_n^{cap} \quad \forall n \in N \quad (7)$$

The parameters in Equation (7) are the same as in Equation (6), except that those in Equation (7) are for the workplace, and an additional factor ( $\alpha_n$ ) is introduced to consider the desired amount of energy to be reserved for upcoming tasks. The value of this parameter can be in the range of [0, 1].

Based on these formulations, the energy available in EVs during weekdays and holidays is shown in Figure 8, along with approximated normal distributions. It can be observed that most EVs can spare around 10 kWh of energy for RaaS during both weekdays and holidays, either at home or at the workplace. It is worth mentioning that all the histograms and density functions are self-normalized. Therefore, a higher mean value at the workplace during holidays could be due to less sample data and random allocation of battery sizes and initial SoC to EVs.



**Figure 8.** Useable energy for RaaS in EVs: (a) home; (b) workplace.

#### 4. Suitability Analysis for Different Types of Buildings

To analyze the suitability of using EVs for RaaS, three cases are considered in this section. In the first case, residential buildings are considered, while in the second case, commercial/industrial buildings are considered. A mix of these two building types with shared parking is considered in the third case. The following equations are used to compute the amount of energy available for RaaS during the weekdays and holidays. The amount of energy available to be used for RaaS during any interval,  $t$  ( $E_t^{RaaS}$ ), can be computed using the following equation:

$$E_t^{RaaS} = \sum_{n \in N} \left( \beta \cdot E_n^{ah} + (1 - \beta) \cdot E_n^{aw} \right) \quad \forall t \in T \quad (8)$$

where  $E_n^{ah}$  and  $E_n^{aw}$  are the available amount of energy to be used for RaaS in EV  $n$  at home and workplace, respectively. Coefficient  $\beta$  is used to determine the ratio of home-based EVs and workplace-based EVs for mixed buildings. For residential buildings,  $\beta = 1$ , and for commercial buildings,  $\beta = 0$ . EVs are randomly selected from the fleet created in the previous section, as given by the following equation:

$$n = \text{rand}([1, N], N_t) \tag{9}$$

This implies that a random sample of size  $N_t$  is selected for each interval of the day. The size of the random sample is computed using the following equation:

$$N_t = \begin{cases} \text{round}(\Gamma_t^h \cdot N \cdot \beta \cdot \gamma^{RaaS}) & \forall t \in T \\ \text{round}(\Gamma_t^w \cdot N \cdot (1 - \beta) \cdot \gamma^{RaaS}) & \forall T \in T \end{cases} \tag{10}$$

where  $\gamma^{RaaS}$  is the ratio of EVs willing to participate in the RaaS, which can take any value in the range of  $[0, 1]$ .  $\Gamma_t^h$  and  $\Gamma_t^w$  are the ratio of vehicles staying at home and workplace, respectively, as given by Equations (1) and (2).

The focus of this study is on analyzing the suitability of EVs to provide RaaS in multi-unit residential buildings/apartments and workplaces, where several residents/workers share a common parking space. Therefore, in this section, a fleet of 25 EVs is analyzed. Sensitivity analysis for different EV fleets is presented in the next section.

#### 4.1. Residential Buildings

In this section, only multi-unit residential buildings are considered, and different participation ratios of EVs are analyzed. For each case, the amount of energy available for RaaS during different hours of the day is analyzed. The participation ratio is varied between 10 and 90%, and nine cases are simulated. In each case, the simulation is repeated 500 times by randomly allocating EVs. The average values of 500 runs are shown in the following figures to provide a generalized picture.

It can be observed from Figures 9 and 10 that with an increase in the participation ratio, available energy also increases, as expected. However, the amount of energy available for different hours of the day is not uniform. For the sake of visualization, the 50% participation case is shown separately in Figure 11. It can be observed that during weekdays, useable energy reduces to a mean of about 60 kWh for the late morning and early evening hours, when a large portion of EV owners is at work. However, the mean energy during the same hours is about 110 kWh for weekends due to the larger number of EV owners staying at home. Nevertheless, a similar average energy value is available for late-night and late-evening hours for both weekdays and holidays. It can be concluded that for a 50% participation of EV owners with 25 home-based EVs, an average of about 60 kWh of backup power can be provided, irrespective of the day type and hour of the day. This is the minimum level of energy that can be provided (corresponding to working days, working hours). During all other intervals, a greater amount of backup can be provided. The lowest value will be the bottleneck and hence the maximum level of backup that can be secured.

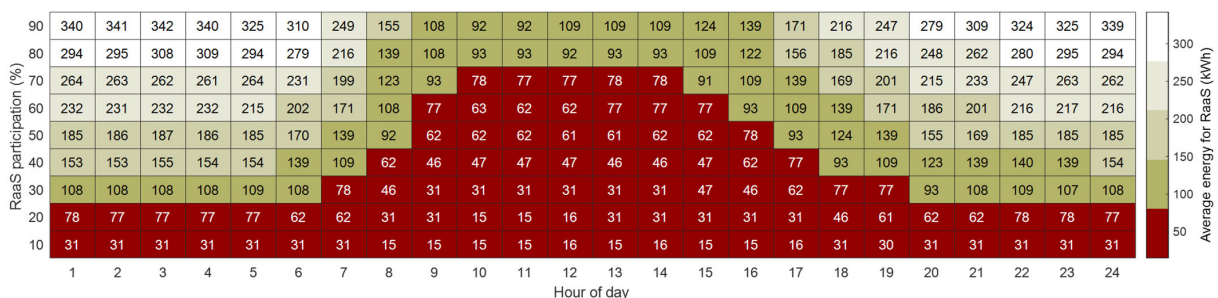


Figure 9. Results of useable energy in residential buildings for RaaS during weekdays.

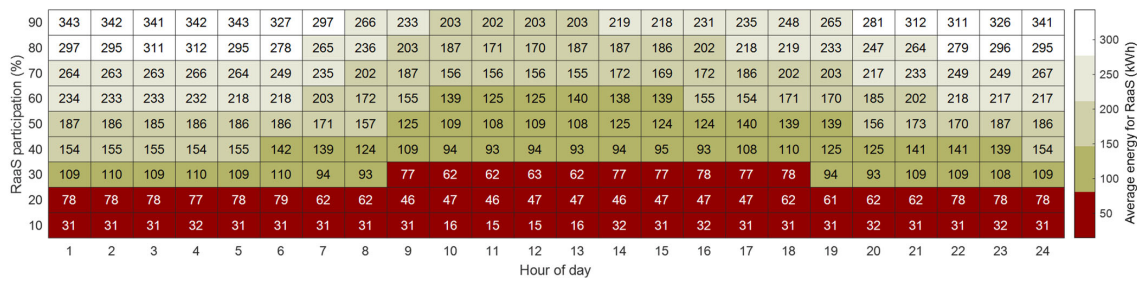


Figure 10. Results of useable energy in residential buildings for RaaS during holidays.

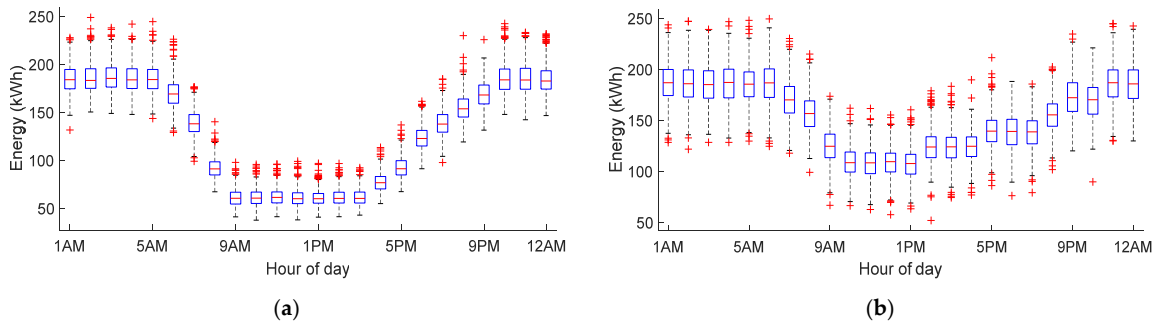


Figure 11. Useable energy in residential buildings for 50% participation case: (a) weekdays; (b) holidays.

4.2. Commercial/Industrial Buildings

Similarly to the residential case, the participation ratio of EV owners is varied between 10 and 90%, and nine cases are simulated for commercial/industrial buildings in this section. Similarly to the previous section, each case is repeated 500 times, and the average results are shown in Figures 12 and 13. It can be observed that during early-morning and late-night hours, none of the EVs is at the workplace. Therefore, the useable energy amount is zero during these intervals, for both weekdays and holidays. However, during working hours, the amount of useable energy increases with an increase in the participation ratio. For the sake of visualization, the 50% penetration case is shown in Figure 14 for weekdays and holidays.

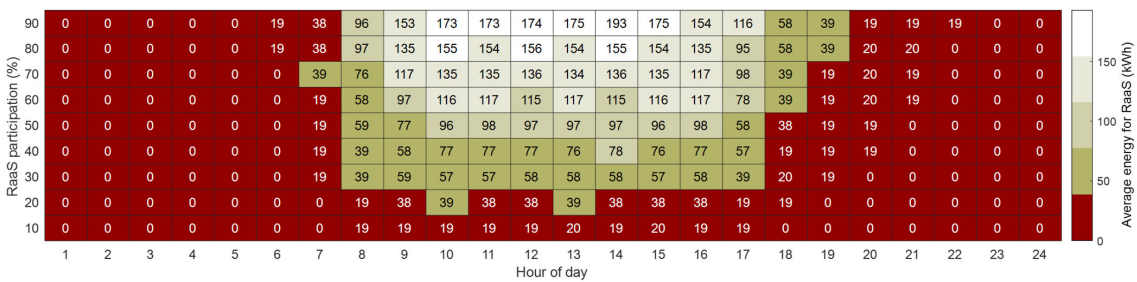


Figure 12. Results of useable energy in commercial/industrial buildings for RaaS during weekdays.

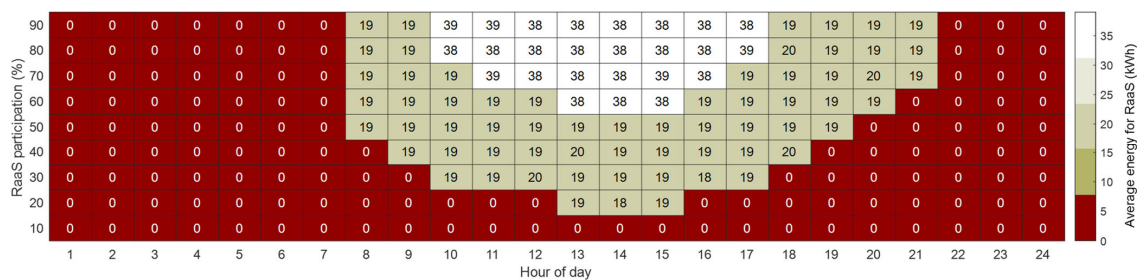
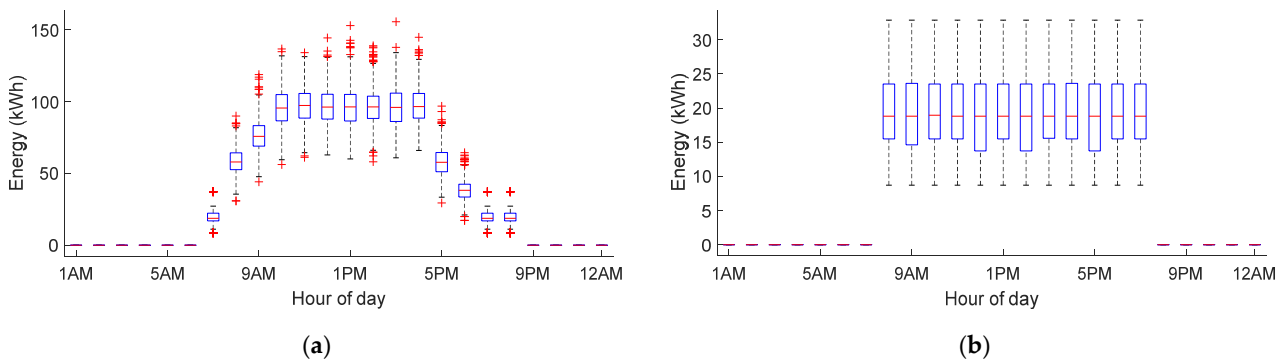


Figure 13. Results of useable energy in commercial/industrial buildings for RaaS during holidays.

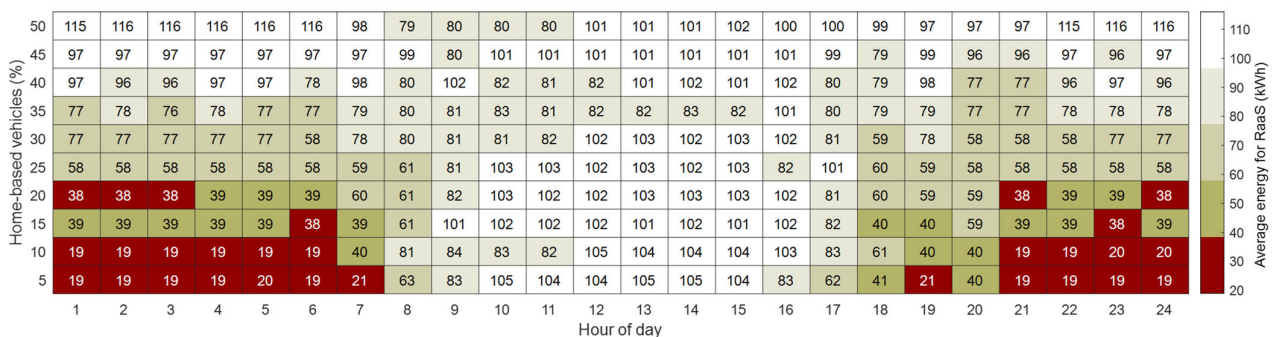


**Figure 14.** Useable energy in commercial/industrial buildings for 50% participation case: (a) weekdays; (b) holidays.

It can be observed from Figure 14 that during non-office hours, none of the EVs is present in the parking lot, and thus, no energy can be used for both weekdays and holidays. However, it is interesting to note that the maximum amount of energy available for RaaS at the workplace with a 50% participation ratio is about 100 kWh, which is significantly less than that available for residential buildings. This is because the ratio of vehicle owners going to work is about 58%; thus, the total number of EVs at the workplace is 15 instead of 25. Similarly, a very minute amount of energy can be provided as a backup during weekends, as depicted in Figure 14. It can be concluded from this analysis that EVs are not suitable to provide RaaS to commercial/industrial-only buildings. With EVs, it is difficult to secure any amount of energy for RaaS in these buildings. For example, during early-morning and late-night hours, none of the EVs is at the workplace, and thus, no energy is available for RaaS. In addition, there is a significant difference in the amount of energy available for RaaS between weekdays and holidays, even during the daytime.

4.3. Mixed Buildings

In this section, an analysis of mixed buildings is carried out, where the parking area is shared by both residential and commercial/industrial buildings. Similarly to the previous cases, a total of 25 EVs are considered in this section, which corresponds to 15 EVs in the workplace. The 50% participation case is considered in this section, and the ratio of home-based EVs ( $\beta$ ) is varied between 5 and 50%, and 10 cases are tested. Therefore, the ratio of workplace EVs will be between 50 and 95%,  $(1-\beta)$  in Equation (10). Simulations for each case are run 500 times, and average results are shown in Figures 15 and 16.



**Figure 15.** Results of useable energy in mixed buildings for RaaS during weekdays.

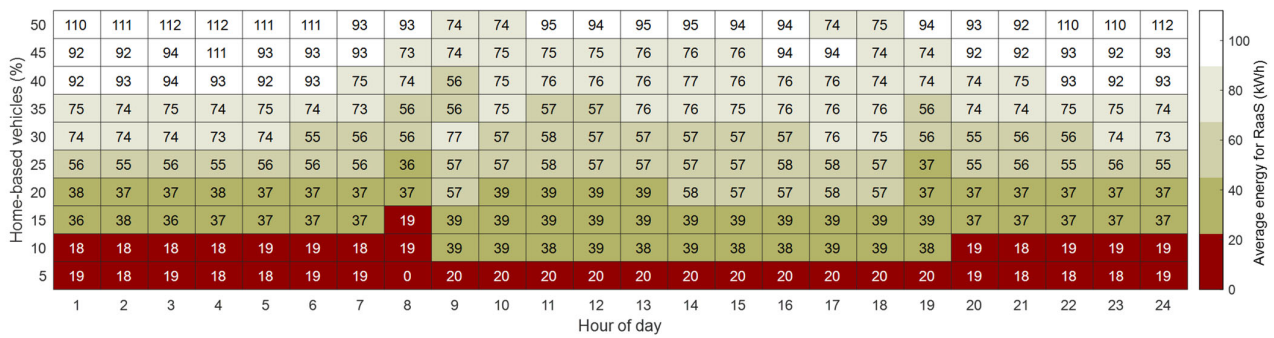


Figure 16. Results of useable energy in mixed buildings for RaaS during holidays.

It can be observed that the amount of energy that can be used during the early-morning and late-night hours increases with an increase in the value of  $\beta$ . However, there is no significant difference during working hours on weekdays. It is worth noting that the difference in the amount of useable energy across different hours of the day is less significant as compared to the previous two cases (residential-only and commercial/industrial-only buildings). This is due to the presence of more EVs in residential areas during nighttime and the presence of more EVs in the workplace during daytime. Therefore, shared parking lots have a higher probability of having EVs present at all times. In particular, the difference is minimal when the value of  $\beta$  is between 35 and 45%.

For the sake of visualization, the 35% case is shown in Figure 17. It can be observed that the fluctuations in the amount of average available energy for RaaS are significantly reduced at different times of the day. Fluctuations are visible only during traveling intervals, i.e., when vehicles are neither at home nor at workplace. It is interesting to note that this is true for both weekdays and holidays. Although during holidays, the number of EVs in the workplace is significantly lower, the number of EVs at home is higher compared to working days. Therefore, the net effect is the same for all days. It can be concluded that for mixed buildings, with 35% home-based EVs, 60 kWh of energy can be provided for RaaS, regardless of the type of day and the hour of the day. This assurance of a certain amount of energy is important for building planners in planning backup power for buildings. Therefore, it can be concluded that mixed buildings are best suited for using EVs to provide RaaS.

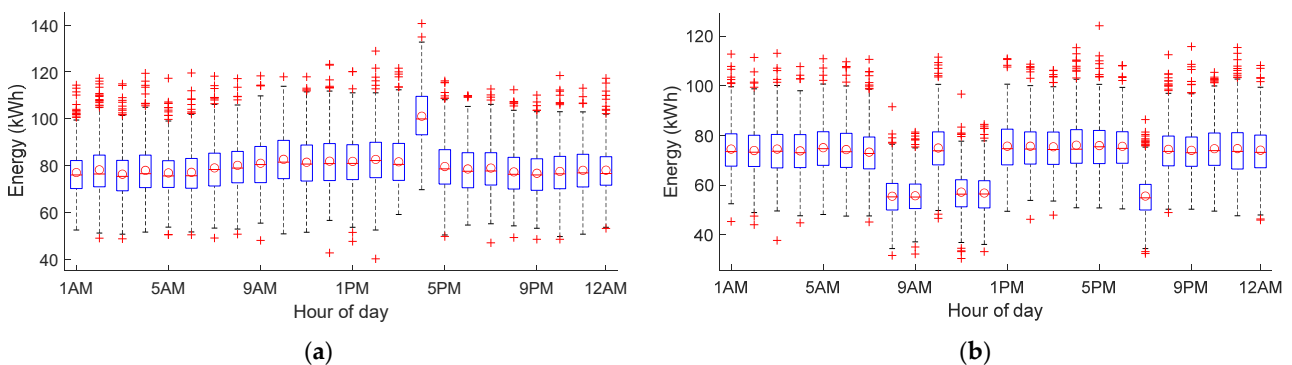


Figure 17. Useable energy in mixed buildings for 50% participation with 35% home-based EVs case: (a) weekdays; (b) holidays.

## 5. Discussion and Analysis

### 5.1. Variation Index for Mixed Buildings

It was demonstrated in the previous section that mixed buildings are suitable for using EVs in the provision of RaaS. However, the main concern of policy makers is to determine the number of EVs to be contracted to ensure a certain amount of backup power throughout the year. In addition, the ratio of EVs from the residential and commercial/industrial sectors

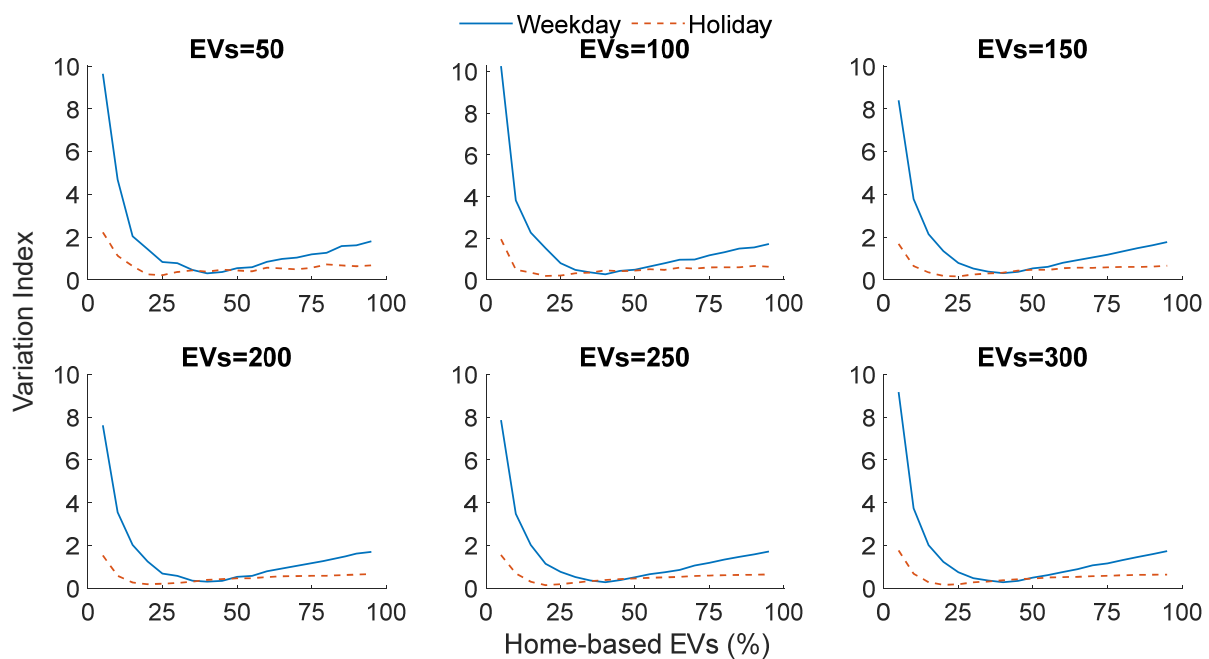


is also of interest in the case of mixed buildings. Therefore, an index is proposed in this study to analyze the desired ratio of home-based and work-based EVs. The proposed variation index ( $V_\beta$ ) shows the variation in the values across different hours of the day. It can be computed using the following equation:

$$V_\beta = \frac{(E_{\beta,\max}^{RaaS} - E_{\beta,\min}^{RaaS})}{(\mu_\beta^{RaaS} - \sigma_\beta^{RaaS})} \quad \forall t \in T \quad (11)$$

where  $E_{\beta,\max}^{RaaS}$  and  $E_{\beta,\min}^{RaaS}$  are the maximum and minimum amount of energy, respectively, for each case, and  $\beta$  is the ratio of home-based EVs. Similarly,  $\mu_\beta^{RaaS}$  and  $\sigma_\beta^{RaaS}$  are the mean and standard deviation, respectively, of the energy for each case. The proposed index shows the difference in the amount of energy available for RaaS under a given EV fleet size. Lower values are desirable since they correspond to lesser variations in the available energy for RaaS. In this section, each simulation is run 1000 times, and means of those values are used for each interval.

It can be observed from Figure 18 that the variation index is lowest when the ratio of home-based EVs is between 30 and 50% in all cases. Although the index is lower for other ratios in the case of holidays, it is not simultaneously lower for weekdays. Therefore, the ratios where the index is simultaneously lower for both weekdays and holidays are considered suitable ratios.



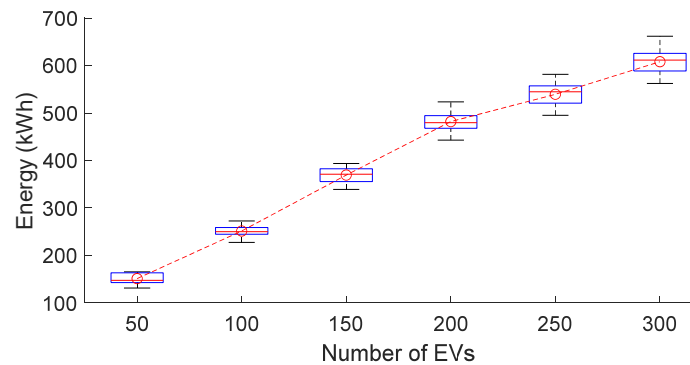
**Figure 18.** Variation index for different EV fleet sizes.

### 5.2. EV Fleet Size and Available Energy for RaaS

The amount of energy available for RaaS in any building is directly proportional to the size of the EV fleet. However, the daily energy consumption and the useable battery size of different EVs are not the same. Similarly, the desired minimum SoC level and the energy required for upcoming trips are also different for different EV owners. Therefore, in this section, the size of the EV fleet is varied between 50 and 300, with a step size of 50, and six cases are simulated. The simulation is repeated 1000 times in each case to visualize the upper and lower bounds of available energy for RaaS.

The available energy for RaaS with this mixed building configuration under different EV fleet sizes is shown in Figure 19. It can be observed that available energy increases

with the EV fleet size, as expected. However, this relationship is not linear throughout the analyzed horizon, which is due to different uncertainties, as discussed in the previous paragraph. In addition, the SoC level and size of EV battery selected for each run are also different due to random selection. It can be concluded from this analysis (50% participation with 35% home-based EVs) that about 6 kWh of energy can be used per participating EV for RaaS.



**Figure 19.** Available energy for RaaS under different EV fleet sizes.

### 5.3. Future Research Directions

Based on the results obtained in this study, further analysis can be carried out to evaluate the useability of EVs to provide RaaS, considering the load characteristics of different buildings. In addition, the presence of EVs in a location (e.g., apartment, school, shopping mall, university, etc.) correlates with the presence of humans, which implies that a greater amount of energy will be required during outages and vice-versa. Therefore, the potential future research directions can be summarized as follows:

- Estimation of optimum EV fleet sizes for different building types, considering the load characteristics, such as load nature (critical vs. non-critical) and magnitude of loads (required duration of backup power).
- Determination of the potential of using EVs for a particular type of commercial/industrial building, considering the correlation between the presence of EVs and the amount of critical load.
- Analysis of the potential of using EVs to provide RaaS to industrial buildings located in the suburbs with poor public transportation systems. This will change the ratio of vehicles used for commuting and, consequently, the amount of energy available for RaaS.

## 6. Conclusions

In this study, the suitability of using electric vehicles to provide reliability-as-a-service for different buildings is analyzed. A large set of driver behavior data is analyzed to extract relevant parameters, and parameters of electric vehicles are extracted from the database of commercially available electric vehicles. Suitability analysis is carried out for buildings that have residential, workplace, and shared parking places. The analysis shows that only commercial/industrial buildings are not suitable to provide reliability-as-a-service during power outages. However, mixed buildings (residential and commercial/industrial) with shared parking spaces are the most suitable building type for using electric vehicles to serve as a backup power source. It is also observed that 30–50% of home-based electric vehicles and the remaining workplace-based vehicles is the desired ratio. These ratios can provide minimum variations in the available energy during different hours of the day for both weekdays and holidays. Finally, it has been shown that each registered electric vehicle can provide about 6 kWh of energy per day towards the backup power pool.

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## Nomenclature

### Abbreviations

BESS	Battery energy storage system
EV	Electric vehicle
NHTS	National Household Travel Survey
RaaS	Reliability-as-a-service
SoC	State-of-charge

### Identifiers

$i$	Identifier for unique vehicles, running from 1 to $I$ .
$k$	Identifier for unique trips, running from 1 to $K$ .
$t$	Identifier for interval of a day, running from 1 to $T$ (24).
$l$	Identifier for number of bin edges (used in daily mileage), running from 1 to $L$ .
$n$	Identifier for EVs, running from 1 to $N$ .

### Parameters and variables

$D_i^{wd}, D_i^{hd}$	Daily mileage of vehicle, $i$ , for weekdays and holidays, respectively.
$V_k^{id}$	Identity of vehicle used for trip $k$ .
$HH_k^{id}$	Identity of the household from where trip $k$ was carried out.
$D_k$	Distance traveled in miles during trip $k$ .
$T_i^{hax}, T_i^{hdax}$	Home arrival and departure time, respectively, $x \in \{w: \text{weekdays}, h: \text{holidays}\}$ .
$T_i^{wax}, T_i^{wdax}$	Workplace arrival and departure time, respectively, $x \in \{w: \text{weekdays}, h: \text{holidays}\}$ .
$T_k^{arr}, T_k^{dep}$	Arrival and departure time, respectively for trip $k$ .
$\Gamma_t^h, \Gamma_t^w$	The ratio of vehicles staying at home and workplace, respectively, during time $t$ .
$R_{ratio}^h, R_{ratio}^w$	The ratio of vehicles returning home and used for commute, respectively.
$f_t^{ha}, f_t^{hd}$	Home arrival and departure probability density, respectively, for time $t$ .
$f_t^{wa}, f_t^{wd}$	Workplace arrival and departure probability density, respectively, for time $t$ .
$F_l$	Histogram value of the daily mileage for bin edge $l$ .
$M_l$	Number of EVs in mileage range corresponding to bin edge $l$ .
$D_l$	Daily mileage for EVs in bin edge $l$ .
$b^w$	Bin width in km, used for daily mileage of vehicles.
$E_n$	Daily energy consumption of EV $n$ .
$E_n^{pkm}$	Energy consumption per km of EV $n$ in Wh.
$E_n^{ah}, E_n^{aw}$	Excess amount of energy available in EV $n$ at home and workplace, respectively.
$E_n^{rh}, E_n^{rw}$	Amount of energy available in EV $n$ at home and workplace at arrival time, respectively.
$SoC_n^{min}$	Preferred minimum level of SoC for EV $n$ .
$B_n^{cap}$	Useable battery size (capacity) of EV $n$ .
$\alpha_n$	Used to define the desired amount of reserve energy for EVs in the workplace for upcoming tasks.
$E_t^{Raas}$	Amount of energy available to be used for RaaS during any interval $t$ .
$\beta$	Used to determine the ratio of home-based EVs and workplace-based EVs for mixed buildings.
$\gamma^{Raas}$	The ratio of EVs willing to participate in RaaS.
$V_\beta$	The proposed variation index.
$E_{\beta, max}^{Raas}, E_{\beta, min}^{Raas}$	The maximum and minimum amount of energy available for RaaS, respectively.
$\mu_\beta^{Raas}, \sigma_\beta^{Raas}$	Mean and standard deviation of energy available for RaaS, respectively.

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