Planning for electric-vehicle evacuations: energy, infrastructure, and storage needs

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***Abstract*— As we advance toward an era of high electric vehicle (EV) adoption, it is critical to address the power requirements for EVs during disaster evacuations, particularly in scenarios of grid failure. This paper provides a comprehensive analysis of the energy needs of EVs during evacuations using a pragmatic stochastic methodology that is both user-friendly and computationally efficient compared to traditional optimization tools. The study evaluates the power requirements of charging infrastructure for various evacuation scenarios, and benchmarks them against the existing infrastructure in several California cities. Additionally, the paper examines the necessary size of backup lithium battery storage to ensure EVs can be adequately powered during evacuations in the absence of grid support. This research offers valuable insights for emergency planners and policymakers to enhance evacuation readiness in the context of increasing EV penetration.**

Keywords—electric vehicles, EV evacuation, energy grid, energy storage, lithium battery

I. Introduction

Natural and human-made disasters are inevitable dangers that often necessitate long-distance evacuations [1]. In 2023 alone, over 3 million Americans were displaced due to such events[1]. In the US, private cars are the primary means of evacuation, as a large fraction of the population owns vehicles [2]. For example, during Hurricane Irma about 90% of people evacuated using their own cars [3] sometimes filling up with gas pumped by gas-powered generators[2].

As we stand at the point of a transportation revolution accelerated by progressive policies, electric vehicles (EVs) are expected to become a dominant mode of transportation. For instance, in the United States, California executive order N-79-20[3] mandates that all new light-duty passenger vehicle sales be zero-emission vehicles (including battery and fuel cell EVs) by 2035. Similarly, Canada set a goal for all new light-duty vehicle sales to be EVs by 2035[4]. Globally, analysts predict a remarkable surge, with > 300 million vehicles light-duty EVs expected by 2035, a tenfold increase from 2021 [4]. Annual sales of light-duty EVs are projected to surpass 70 million by 2035, making up 68% of all light-duty vehicle sales[5]. How will these vehicles be powered during emergency evacuations?

Feng et al. [5] analyzed Hurricane Irma in 2017 in Florida and found that if a significant portion of vehicles were EVs, the state would face a serious challenge in powering them during evacuation. Adderly et al. [1] also highlighted this challenge and encouraged policymakers to incorporate more EV charging stations along known evacuation routes into their plans. Thus, the literature underscores that developing a robust plan for emergency evacuations in an era of widespread EV adoption is crucial, especially considering potential grid failures. For instance, California has implemented power shutoffs during high winds to mitigate wildfire risks, making the challenge of powering EVs during evacuations more severe[6].

To the author's knowledge, the current literature does not provide local officials and emergency managers with tools to quickly understand the energy needs of EV evacuations at a regional or state level, nor how to assess the adequacy of the energy infrastructure. This paper addresses that gap by presenting a pragmatic stochastic method for estimating the energy needs for EVs during evacuation and the power needs of charging infrastructure. Various EV evacuation scenarios are explored and presented in such a way that local officials and planners can use the results to apply to their own situations as a function of the number of EVs, the distance to be driven, and the speed of the evacuation. For emergencies that also involve loss of grid power, the needed size of storage is also presented.

II. Methodology

This study first focuses on the macro-level analysis of the energy needs to move EVs from the danger zone (origin) to a safe area (a shelter, hotel or the house of a family member). Subsequently, we use the calculated energy needs to estimate charging infrastructure backup storage needs for different evacuation cases. Fig. 1 provides a schematic of the key parameters involved in the calculations.

[1] https://www.urban.org/urban-wire/more-3-million-americans-were-displaced-natural-disaster-past-year-how-can-we-prepare

[2] https://www.abcactionnews.com/simplemost/how-do-gas-stations-pump-without-electricity

[3] https://www.gov.ca.gov/wp-content/uploads/2020/09/9.23.20-EO-N-79-20-Climate.pdf

[4] https://tc.canada.ca/en/road-transportation/innovative-technologies/zero-emission-vehicles/canada-s-zero-emission-vehicle-sales-targets

[5] https://www.ev-volumes.com

[6] https://www.newsweek.com/california-shuts-off-power-wildfire-risk-1920790

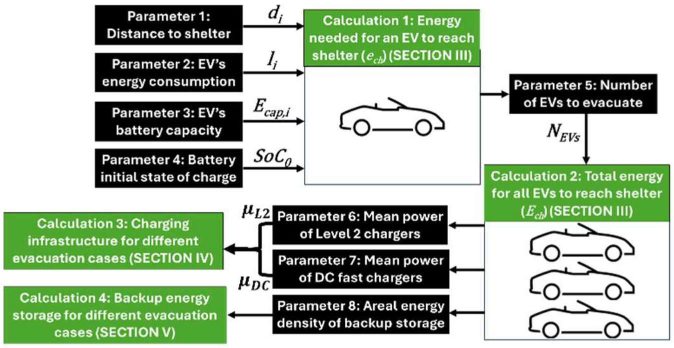

Fig. 1. Overview of this study's methodology to estimate the charging energy, charging infrastructure, and backup storage needs for evacuation scenarios.

III. Estimating Evacuation Energy Demand

A. Evacuation Energy Needs

Considering the evacuation of a geographic area with N_{EV} EVs, we assume that each vehicle i, where i is an integer between 1 and N_{EV}, needs to drive d_i km to reach a shelter. The energy e_i kWh required to evacuate each vehicle is given as:

$$e_i = l_i d_i \tag{1}$$

where l_i (kWh/km) is the energy consumption of the vehicle per distance driven. The energy capacity of the battery in vehicle i is denoted as $E_{cap,i}$ kWh and the initial SoC defined as $SoC_0 \in [0,1]$. If the energy available in the vehicle ($=E_{cap,i}SoC_0$) is less than e_i, then the evacuee will need to charge the vehicle (one or more times) to reach the destination. The amount of charging energy $e_{ch,i}$ is given as:

$$e_{ch,i} = \max(e_i - SoC_0 \times E_{cap,i}, 0) \tag{2}$$

The total energy to charge all EVs is defined as

$$E_{ch} = \sum_{i=1}^{N_{EV}} e_{ch,i} \tag{3}$$

Computing E_{ch} is not easy. There are several sources of uncertainty in the parameters ($N_{EV}, d_i, l_i, E_{cap,i}, SoC_0$). For example, we do not know in advance if everybody will follow the evacuation orders, affecting N_{EV}. The distance to the destination also depends on each user. Some users, especially from financially disadvantaged groups, may need to go to public shelters, while others may prefer to go to hotels or join family members. The normalized energy consumption l_i and battery usable energy $E_{cap,i}$ vary from vehicle-to-vehicle depending on its size, energy efficiency and velocity.

To deal with these uncertainties, we treat the above parameters as random variables characterized by probabilistic distributions, as introduced in the next sub-section.

[7] https://ev-database.org

B. Capturing uncertainty via Probabilist Distributions

The distance to safe area, d_i, is parameterized with a triangular distribution $\mathbf{T_d}\,(d_{min}, d_{mode}, d_{max})$ with a lower limit d_{min}, an upper limit d_{max} and a mode d_{mode}. We selected this distribution because it is easy to parameterize by the end user or the planning agency. The user can define the minimum distance to the shelter (d_{min}), the maximum distance that people may drive (d_{max}) as well an educated guess for the modal value (d_{mode}). Fig. 2 provides hypothetical examples for the triangular distributions used in this study.

To obtain l_i, we considered the efficiencies of 360 EVs currently available in the market[7] – see histogram in Fig. 3. The energy efficiency varies from 139 Wh/km (Tesla Model 3) to 322 Wh/km (Mercedes-Benz G580). To approximate the uncertainty, we fit the histogram with a Gaussian distribution, obtaining a mean energy efficiency of μ_l=0.188 kWh/km and a standard variation σ_l= 0.025 kWh/km. The energy efficiency is sampled from this distribution $l_i \sim \boldsymbol{N}_l(\mu_l, \sigma_l^2)$.

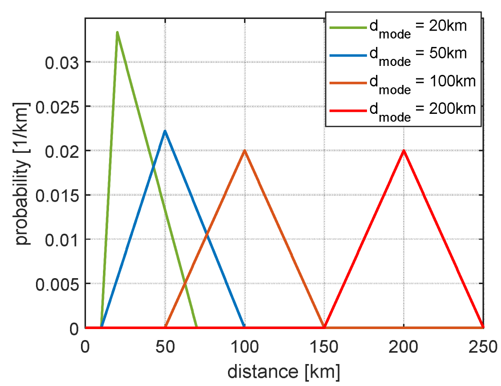

Fig. 2. Example triangular distributions for driving distance to safe zone (d_i).

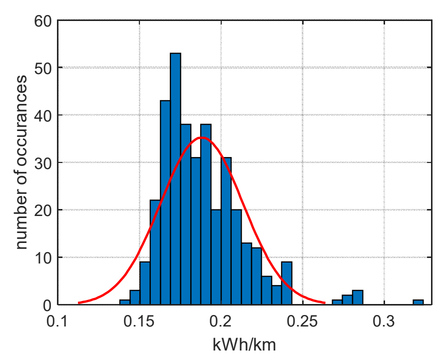

Fig. 3. Histogram of the energy efficiency (l_i) for 360 battery EVs currently on the market[7]. Red line indicates a Gaussian distribution fit to the histogram.

Fig. 4 depicts the histogram of the energy capacities for the 360 EV's in the database[7]. The energy capacity varies from 21.3 kWh for the Renault Twingo Electric up to 123 kWh for the VinFast VF 9 Extended Range. When fitting a Gaussian distribution, we obtained a mean value of $\mu_C = 74.7$ kWh and standard deviation $\sigma_C = 20.8$ kWh. The battery energy capacity is sampled from $E_{cap,i} \sim \boldsymbol{N_C}(\mu_C, \sigma_C^2)$.

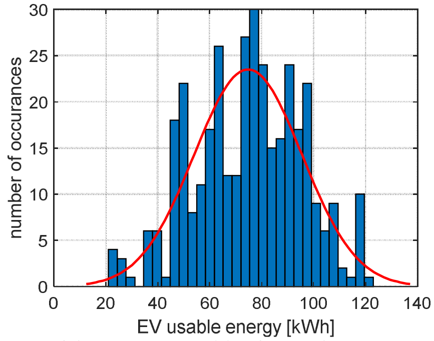

Fig. 4. Histogram of the energy capacities for 360 battery EVs currently on the market[7]. Red line indicates the Gaussian distribution we used for ($E_{cap,i}$)

The initial state of charge SoC_0 is another crucial parameter that affects the evacuation. We assume that SoC_0 belongs to a triangular distribution

$$SoC_0 \sim \mathbf{T}_{\boldsymbol{SoC0}} \left(SoC_{0,min}, SoC_{0,mode}, SoC_{0,max}\right) \quad (4)$$

where $SoC_{0,min}$ is the SoC of the battery is fully depleted and $SoC_{0,max}$ is the SoC when the battery is fully charged. In what follows we consider three scenarios

i) *Pessimistic* scenario ($SoC_{0,mode} = 0.1$), where most of the EV users start with low SoC.
ii) *Average scenario* ($SoC_{0,mode} = 0.5$), where most of the EV users have 50% SoC available at the time of the evacuation
iii) *Optimistic scenario* ($SoC_{0,mode} = 0.9$), where most of the vehicles are close to full charge.

Fig. 5 depicts the probabilistic distributions for the scenarios.

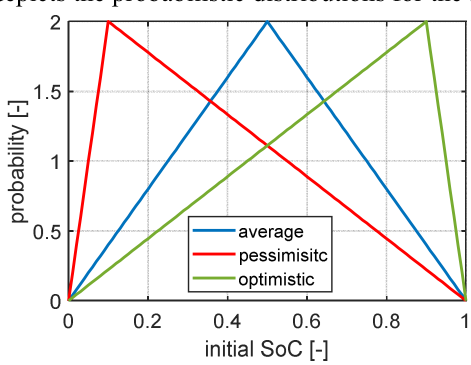

Fig. 5. Probability distributions of the initial state of charge of the EV (SoC_0) before the evacuation.

C. Preliminary Results

Using the above framework, the total energy needed for the evacuation becomes a function of multiple random variables $d_i, l_i, E_{cap,i}, SoC_0$ as defined by equations 1-3. To evaluate E_{ch} we employ a Monte Carlo simulation approach, where the random variables are sampled from the probabilistic distribution introduced in the previous section. All the parameters are summarized in Table 1 in the appendix.

Fig. 6 shows the histogram of E_{ch} for $d_{mode} = 150$ km, and the *average scenario* for the initial *SoC*. To facilitate the translation to other evacuation cases, we normalized the total energy by $N_{EV} = 1000$ EVs. We note that, despite the mix of triangular and Gaussian probabilistic distributions, the overall trend of the histogram of E_{ch} is similar to a Gaussian curve. We denote the mean of this Gaussian approximation as $\hat{E}_{ch}$.

Fig. 7 depicts the mean value $\hat{E}_{ch}$ for different values of d_{mode} and initial SoC scenarios. The results show a clear trend: as we increase the evacuation distance (d_{mode}) or have lower initial SoC the total energy demand increases. This is in line with our expectations.

It is worth noticing that the impact of d_{mode} and initial SoC in $\hat{E}_{ch}$ is nonlinear. The gradient of $\hat{E}_{ch}(d_{mode})$ becomes progressively larger as the evacuation distance increases. The *initial SoC* also plays a key role in the total energy. For example, assuming $d_{mode} = 100\ km$ and an *average initial SoC,* we will need approximately 1.3 MWh per 1k EVs. In the *pessimistic initial* SoC scenario, the total charging energy increases threefold to 3.6 (MWh/1k EVs). The standard variation of E_{ch} also increases with the evacuation distance.

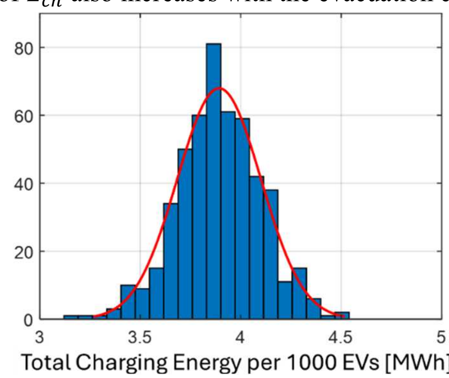

Fig. 6. Histogram of the total energy for charging, E_{ch}, assuming $d_{mode} =$ 150 km, average initial SoC ($SoC_{0,mode} = 0.5$) and $N_{EV} = 1000$.

These plots of *charging Energy vs evacuation distance vs initial SoC* illustrated in Fig.7 can help local emergency services deal with different evacuation scenarios. The evacuation distance may depend on the type of natural hazard and location. For example, the state of Florida, USA is often affected by hurricanes, leading to massive evacuations, sometimes involving long-distance evacuations to out of state[8]. Other natural disasters may require a shorter range. For example, in 2023, Merced County in California (where the authors reside) issued several evacuation warnings asking residents of Planada to leave due to flooding[9]. The distance from Planada to Merced's shelter is less than 15 km.

Another important variable is the number of vehicles that need to be evacuated (N_{EV}). Fig. 8 shows the estimated mean $\hat{E}_{ch}$ as N_{EV} increases from 1k cars to 1 million (assuming $d_{mode} = 100\ km$ and different initial SoC). We observe that:

- Evacuation of a small neighborhood with 1000 EVs will require 0.8 to 3.6 MWh of energy.

[8] https://www.fl-counties.com/sites/default/files/2018-02/Evacuations%20Report.pdf

[9] https://calmatters.org/california-divide/2023/11/planada-flood-relief/#:~:text=Days%20of%20rain%20led%20to,of%20Planada%2C%20population%20almost%204%2C000.

- A small city of 100,000 EVs will need 76 to 362 MWh
- A large city with 1 million cars will need GWh-level of energy to support the evacuation.

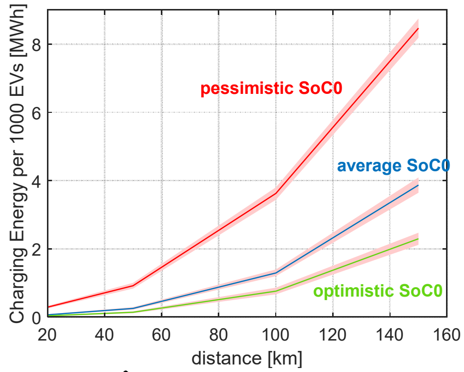

Fig. 7. Representation of $\hat{E}_{ch}$, the estimated mean value of total energy E_{CH}, for different evacuation distances (d_{mode}); the standard deviation is captured by the confidence bounds around the mean.

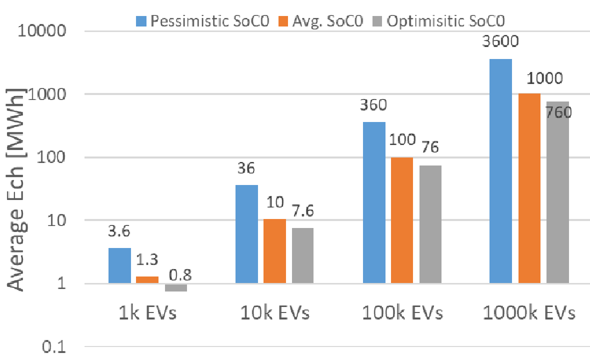

Fig. 8. $\hat{E}_{ch}$, the estimated mean value of total energy E_{CH}, when scaling the evacuation from 1k cars to 1000k for three initial SoCs (with d_{mode} = 100 km).

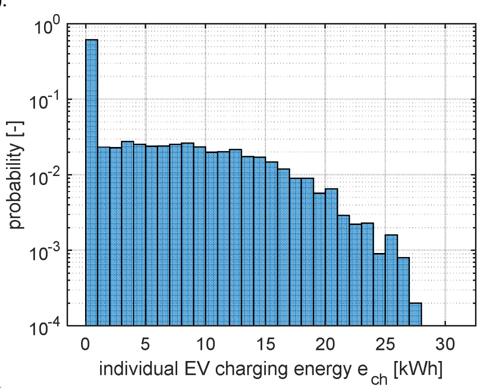

Fig. 9. Histogram of the charging energy e_{CH} for each vehicle (d_{mode} = 100km, and pessimistic SoC_0). The vertical axis uses a logarithmic scale.

Finally, Fig. 9 shows the histogram of e_{ch} for d_{mode} = 100 km and a *pessimistic* initial SoC. It is interesting to note that in this scenario, more than 60% of EVs will require a negligible amount of charging energy (less than 1 kWh); they can reach the shelter with the initial energy in the EV battery and do not need to stop for recharging. The remaining 40% of evacuees will need to stop to charge the EV batteries, requiring up to 30 kWh of additional energy to reach the shelter.

[10] https://web.stanford.edu/~boyd/cvxbook/bv_cvxbook.pdf

IV. Estimating Infrastructure for an Evacuation

The previous section provided an estimate on the charging energy needed to support the evacuation. Next, we analyze the charging infrastructure and develop insights into the minimum number of EV charging stations necessary to support the evacuation. Let us consider E^*_{ch} kWh as the charging energy needed for the evacuation. Assume a window of T_{eva} (in h) to perform the evacuation and leave the danger zone. The average charging power needs for the evacuation is defined as:

$$p^*_{CH} = \frac{E^*_{ch}}{T_{eva}} \tag{5}$$

This power can be transmitted to the EVs via a Level 2 charger or DC fast charger (Level 1 charging is assumed to be too slow for evacuations). We define $n_{L2} \geq 0$ as the number of Level 2 charging stations and $n_{DC} \geq 0$ as the number of DC fast charging stations. The power capability of each individual charger is assumed to have a Gaussian distribution:

$$p_{L2,j} \in N(\mu_{L2}, \sigma^2_{L2}) \tag{6}$$

$$p_{DC,k} \in N(\mu_{DC}, \sigma^2_{DC}) \tag{7}$$

where $j \in \{1,2,..n_{L2}\}$ and $k \in \{1,2,..n_{DC}\}$, μ_{L2} and μ_{DC} represent the mean power of the chargers and $\sigma^2_{L2}, \sigma^2_{DC}$ their variance. This distribution may vary from region to region depending on the charging network available in each community. Table 1 in Appendix tabulates the values used here.

The overall charging power available in the evacuation region is defined as

$$p_{CH} = \sum_{k=1}^{n_{DC}} p_{DC,k} + \sum_{j=1}^{n_{L_2}} p_{L2,j} \tag{8}$$

Since we are adding Gaussian random variables, the total charging power fulfills $p_{CH} \sim N(\mu_{CH}, \sigma^2_{CH})$, with

$$\mu_{CH} = n_{DC}\mu_{DC} + n_{L2}\mu_{L2} \tag{9}$$

$$\sigma^2_{CH} = n_{DC}\sigma^2_{DC} + n_{L2}\sigma^2_{L2} \tag{10}$$

We would like to guarantee that the charging power is fulfilled with a certain probability guarantee. We formulate this requirement as:

$$prob(p_{CH} \geq p^*_{CH}) \geq \beta \tag{11}$$

where $\beta \in [0,1]$ corresponds to the probability of delivering the required charging power; β should be close to 1. This probability can be re-written as[10]:

$$prob(p_{CH} \geq p^*_{CH}) = 1 - \phi(\frac{p^*_{CH} - \mu_{CH}}{\sigma_{CH}}) \tag{12}$$

where $\phi(.)$ is the cumulative distribution function of the normalized Gaussian distribution $N(0,1)$. Combining the two previous equations allows us to express the probabilistic constraint as:

$$\mu_{CH} + \sigma_{CH}\phi^{-1}(1-\beta) \geq p^*_{CH} \tag{13}$$

From a planning perspective, we would like to know if n_{L2}, n_{DC} is enough to fulfill p^*_{CH}. This requirement can be translated to the set:

$$\Gamma(\beta, p_{CH}^{*}) = \{(n_{L2}, n_{DC}):\ n_{DC}\mu_{DC} + n_{L2}\mu_{L2} \geq p_{CH}^{*} - \\ +(n_{DC}\sigma_{DC}^{2} + n_{L2}\sigma_{L2}^{2})^{\frac{1}{2}}\phi^{-1}(1-\beta)\} \quad (14)$$

where $\Gamma(\beta)$ represents the set of all feasible combinations of Level 2 and DC fast charging stations that can fulfill p_{CH}^{*}. Note that computing the above set analytically is not straightforward because of the nonlinear dependence in n_{L2}, n_{DC}. An approximation of this set can be easily generated when $\beta = 1/2$ (leading to $\phi^{-1}(1/2) = 0$).

$$\hat{\Gamma}(\, p_{CH}^{*}) = \{(n_{L2}, n_{DC}):\ n_{DC}\mu_{DC} + n_{L2}\mu_{L2} \geq p_{CH}^{*}\} \quad (15)$$

This approximation only considers the mean charging powers and neglects uncertainties. Fig. 10 provides a graphical illustration of $\Gamma(\beta, p_{CH}^{*})$ when $\beta = 0.98$ and $p_{CH}^{*} = 50\,(\frac{MWh}{4h}) = 12.5MW$, as well as the boundary of the $\hat{\Gamma}$. One can conclude that $\Gamma(\beta, p_{CH}^{*}) \subset \hat{\Gamma}(p_{CH}^{*})$ for this parameterization. The set $\Gamma(\beta, p_{CH}^{*})$ provides a more conservative estimate for the number of charging stations, which considers uncertainty in the charging power. This property holds as long as $\beta \geq 0.5$, as demonstrated in the next result.

Lemma: $\Gamma(\beta, p_{CH}^{*}) \subset \hat{\Gamma}(p_{CH}^{*})$ if $\beta \geq 0.5$(Proof: See appendix).

Fig. 11 shows $\hat{\Gamma}(p_{CH}^{*})$ for power-requirement scenarios ranging from 1 to 50 MW using logarithmic plots. The plot also includes symbols indicating the current EV charging available in several cities in California, which was obtained from[11].

In Mariposa County, a region with a population of approximately 17,000, the current infrastructure can provide up to p_{CH}^{*} =~2.5 MW of EV charging power. More populated counties, such as San Francisco (>0.8M people) and Sacramento (1.5M people), can provide significantly more charging power, 30 MW and 36MW, respectively. In order to estimate the minimum evacuation time, we assume i) one EV per 2 evacuees (this means 8.5k EVs for Mariposa); ii) an *average SoC_0*, and evacuation distance $d_{mode} = 100$ km (according to Fig.7, this means 1k EVs require 1 MWh of charging energy; i.e., 8.5 MWh of charging energy for Mariposa). The total charging time for Mariposa is $T_{ch} = \frac{E_{ch}^{*}}{p_{CH}^{*}} = 3.4$ h, while Sacramento needs $T_{ch} = \frac{E_{ch}^{*}}{p_{CH}^{*}} = \frac{(\frac{1500}{2})MWh}{36\,MW} = 20.8$ h. This result indicates that Sacramento is under prepared for a large-scale EV evacuation with short window. Some natural hazards, such as wildfire, may only provide a few hours of preparation before the evacuation. Figures 10 and 11 allow planning agencies to quickly check the adequacy of their current charging infrastructure.

Limitation: this analysis does not consider where the evacuee will charge or when. This simplified analysis assumes that everyone can "perfectly" synchronize the timing to access the charging stations. We also neglect time to change cars between charging sessions and distance to reach the charging stations. This analysis provides an "absolute" lower bound for the number of charging stations needed for the evacuation.

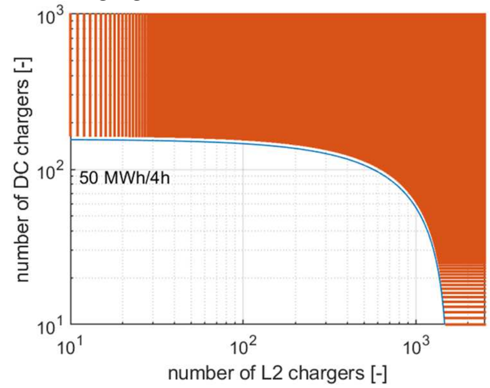

Fig. 10. Representation of $\Gamma(\beta = 0.98, p_{CH}^{*})$--the red set -- and the boundary of the approximation $\hat{\Gamma}$ for $p_{CH}^{*} = \frac{50MWh}{4h} = 12$ MW.

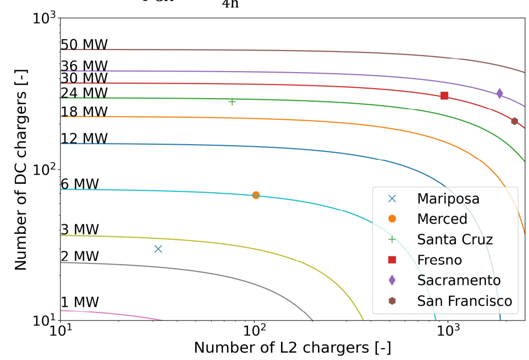

Fig. 11. Boundary of $\hat{\Gamma}(p_{CH}^{*})$ for different charging power requirements p_{CH}^{*}.

V. Backup Energy Storage

Up to now, we assumed that the charging stations have continuous access to electrical energy. During emergency evacuations, this assumption may not hold. For example, charging power may not be available as a result of damage to the electrical infrastructure or shutdown initiated by the electrial utility (e.g. to prevent ignition of wildfires). If grid power is not available, communities may need to rely on backup power generation or storage to charge the EVs.

This section analyzes the area requirements of backup energy to support evacuation of EVs. Lithium batteries are selected for this analysis because they are already in use at fast-charging stations[12] [6]. This backup storage can be utilized and generate revenue during non-evacuation times, with the understanding that it should be fully charged and reserved when a disaster is predicted. Alternatively, the storage system can be isolated and kept in standby mode until an evacuation is necessary. In this scenario, the storage system's idle loss, the rate at which energy is lost while in storage, becomes

[11] https://www.energy.ca.gov/data-reports/energy-almanac/zero-emission-vehicle-and-infrastructure-statistics-collection/electric

[12] https://l-charge.net/services/

significant. The idle loss for lithium batteries is approximately 0.2% per day, according to measurements[13,14].

Based on available market products, the areal energy density for lithium batteries is 160-570 (kWh/m^2) [15, 16]. According to Fig. 12, the size of storage varies significantly with the scale of the evacuation. For instance, evacuating a small neighborhood with 1,000 EVs over a distance of 100 km might require up to 3.6 MWh of storage, an amount that could be trucked in. On the other hand, a large city with 1 million EVs could require GWh-level storage solutions, a size that is currently available in only a handful of locations in California.

Limitation: This analysis does not account for ground coverage ratios (GCR). For instance, if the GCR is 50%, the actual land area required for all storage systems depicted in Fig. 12 would need to be doubled.

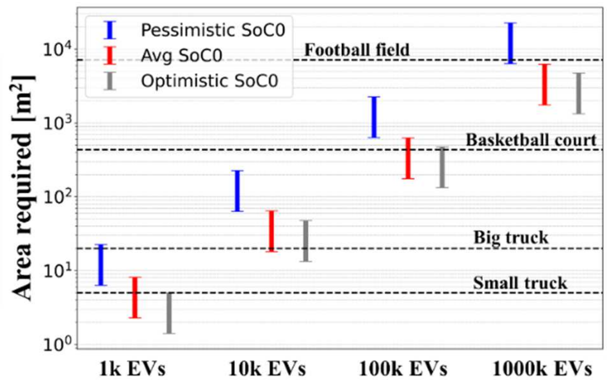

Fig. 12 – Backup storage required area m^2 when scaling the evacuation from 1k cars to 1000k for different initial SoCs (with $d_{mode} = 100$ km).

VI. Conclusions

This study comprehensively analyzed the total energy needs for charging electric vehicles (EVs) during evacuations caused by disasters. The study examined the impact of five key parameters in this problem, including: distance to shelter, EV energy consumption, EV battery capacity, the initial state of charge of EV batteries, and the number of EVs to evacuate. The study uses a pragmatic stochastic methodology to capture the uncertainty in these key parameters.

Furthermore, a comparison of the existing charging infrastructure with that needed for many of the evacuation scenarios suggests that some California counties already have an adequate number of charging stations for some scenarios, but additional chargers, particularly fast chargers, will be useful for larger evacuations or ones that need to be executed quickly.

Finally, for grid failure cases, the required size of backup local energy storage solutions, especially lithium battery systems, is analyzed for different evacuation scenarios. The size of storage varies significantly with the scale of the evacuation. The graphs provide planners with easy-to-use tools for estimating the number of chargers (Figs. 10 & 11) and the size of back-up storage (Fig. 12) that could be needed for their cities.

Acknowledgment

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Appendix

TABLE 1. Parameters Used or Calculated in the Analysis of the Evacuation Scenarios

	Description	Value
N_{EV}	Number of EVs	1, …, 1M
d_{mode}	Most common evacuation distance	20, …, 200
d_{min}	Minimum evacuation distance	max(10, $d_{mode} - 50$)
d_{max}	Maximum evacuation distance	$d_{mode} + 50$
μ_l	Average energy efficiency	0.188 (kWh/km)
σ_l	Standard deviation for energy consumption	0.025 (kWh/km)
μ_C	Average battery capacity of the EV	74.7 (kWh)
σ_C	Standard deviation of the battery capacity	20.8 (kWh)
$SoC_{0,mode}$,	Most common initial SoC	{0.1, 0.5, 0.9}
$SoC_{0,min}$	Minimum initial SoC	0
$SoC_{0,max}$	Maximum initial SoC	1
μ_{L2}	Mean power of Level 2 chargers	6 (kW)
μ_{DC}	Mean power of DC fast chargers	80 (kW)
σ_{l2}	Standard deviation of Level 2 chargers' power	3 (kW)
σ_{DC}	Standard deviation of DC fast chargers' power	20 (kW)

Proof of the Lemma: pick any pair $(n_{L2}^*, n_{DC}^*) \in \Gamma(\beta)$. We would like to show that $(n_{L2}^*, n_{DC}^*) \in \hat{\Gamma}$. To demonstrate this, we note that the pair (n_{L2}^*, n_{DC}^*) fulfills:

$$n_{DC}^*\mu_{DC} + n_{L2}^*\mu_{L2} \geq p_{CH}^* - \theta$$

where $\theta = (n_{DC}\sigma_{DC}^2 + n_{L2}\sigma_{L2}^2)^{\frac{1}{2}}\phi^{-1}(1-\beta)$. Note that since $\beta \geq 0.5$ the argument of ϕ^{-1} is inferior to 0.5. As a result $\phi^{-1}(1-\beta) \leq 0$ and $\theta \leq 0$, leading to

$$n_{DC}^*\mu_{DC} + n_{L2}^*\mu_{L2} \geq p_{CH}^*$$

as a result $(n_{L2}^*, n_{DC}^*) \in \hat{\Gamma}$

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