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EARTHQUAKE RESILIENCE OF DISTRIBUTED ENERGY RESOURCES

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Abstract

Distributed energy resources (DERs) are expected to increase the resilience of power systems to natural disasters by introducing multiple power-generation and -storage units in close proximity to users. This paper evaluates the increase in post-disaster power accessibility spurred by the rapid adoption of DERs and the potential deployment of microgrids in San Carlos, California. We used a recently developed methodology that quantifies the power-generation performance of microgrid clusters and households with rooftop solar panels after earthquakes. Additionally, we leveraged a novel high-resolution dataset on the current household adoption of solar panels, estimated using computer vision and satellite imagery. Our results show that the current adoption of 8.5% is insufficient to supply enough power to households in San Carlos after a magnitude 8.0 earthquake. We also show that for adoptions higher than 20%, microgrid clusters can effectively provide sufficient post-earthquake power accessibility during the summer season in San Carlos; however, during other seasons higher adoption or other measures might be necessary. Our results indicate that under net-zero policies, the aggregated post-earthquake solar generation strongly relies on households with high power consumption because they introduce the largest solar panel arrays to the community. Finally, our results demonstrate that when adoption is more uniformly distributed across microgrids, the risk of not meeting post-earthquake power demands has significantly less variability.

Keywords: earthquake resilience, solar panels, microgrids, power systems

1. Introduction

Traditional power systems often experience massive failures after extreme natural events. For example, Hurricane Maria caused one of the longest and largest power outages in modern U.S. history [1], which affected more than eight million people. Because traditional power systems are particularly vulnerable to these events, the rapid adoption of distributed energy resources (DERs) provides an invaluable opportunity to increase the power system resilience.

DERs are rapidly transforming the traditional, centralized power system into a decentralized one that incorporates multiple generation sources (e.g., rooftop solar) and storage units in close proximity to end users. In the U.S., rooftop solar installations have increased at a 7.5% rate [2], and projections indicate that solar generation will be 20-30% of the global electricity by 2050 [3]. Additionally, governments are building roadmaps for the deployment of microgrids, which are a cluster of DERs and power loads that can connect to and disconnect from the main power grid. The Roppongi Hills and the Sendai microgrids have already shown that microgrids can improve the resilience of power systems when they disconnected from the main grid and functioned as secure power islands after the 2011 Tohoku earthquake and tsunami in Japan [4]. This evidence and recent studies indicate that DERs and microgrids can be effective for power system resilience. However, until recently, studies have not been able to quantify the increase in post-disaster power accessibility introduced by DERs because of two issues. First, there has been a lack of methodologies for such a quantification of post-disaster power availability. And second, there has been a lack of high-resolution DER data to link power-generation capacity with the disaster vulnerability of the supporting infrastructure, for example, the seismic vulnerability of buildings in the case of rooftop solar generation after earthquakes.

Two recent investigations addressed these two fundamental issues. First, Patel et al. (2019) developed a quantitative methodology to evaluate risk metrics on post-disaster power accessibility in communities with rooftop solar panels and microgrid clusters [5]. Second, Yu et al., (2018) developed a computer vision algorithm that identifies location and sizes of rooftop solar panels from satellite imagery [6].

with high accuracy. In this paper, we summarize the methodology developed by Patel et al. (2019) and leverage the high-resolution estimates of current solar adoption to quantify power accessibility in San Carlos, California, during the aftermath of a magnitude 8.0 earthquake representing the 1906 San Francisco event. We also provide recommendations to guide the deployment of rooftop solar panels and microgrids for improved resilience of the power system.

2. Formulation for Disaster Resilience of DERs

Patel et al. (2019) provide the complete description of the formulation for disaster resilience of DERs [5]. In this section, we include a summary of this formulation to provide background for this paper.

2.1. Risk definition

We first define a microgrid cluster as a group of homes that cooperate to share energy in case of a main grid outage. For each home that belongs to a cluster, we define "risk" as the probability that when a catastrophic event causes a power outage, the homes in the cluster will be not able to generate enough energy to meet their reduced load for at least one day during the outage. Formally, this risk can be defined as in Eq. (1), where C is the catastrophe, V_j is the cluster of homes, T is the period of analysis (e.g., whole year or a particular season), $\hat{s}$ is the span of outage randomly chosen from period T, $l_{i,d}$ is the electrical energy consumption by home H_i on day d, f is the load reduction factor after the catastrophe, and x_i is the indicator of home habitability after the catastrophe (1 for uninhabitable after event C and 0 otherwise).

$$R(V_j, T, C) = P\left[\bigcup_{d\in\hat{s}}\left(\sum_{H_i\in V_j} f \times l_{i,d} > \sum_{H_i\in V_j}(1 - x_i(C))e_{i,d}\right)\right] \tag{1}$$

The empirical estimate of risk is generated using actual realization of daily load and daily solar generation for each household, as well as multiple Monte Carlo realizations of building damage due to earthquake shaking. As mentioned previously, the complete formulation for the empirically estimated risk can be found in Patel et al. (2018) [5].

3. Application to a Magnitude 8.0 Earthquake affecting San Carlos, California

3.1. Variations studied

The two variations of solar adoption rules that were considered in Patel et al. (2019) [5] are also presented in this paper: overall adoption and even adoption. Under the overall rule, the first adopters are the households that have the largest electric savings as a result of the solar adoption across all clusters, whereas under the even rule, the first adopters are also the households with the largest savings but within each cluster separately. If the adoption rate r is the fraction of homes that have adopted rooftop solar, and N is the total number of homes in each cluster, the total number of adopters will be rN. The adoption rule determines which rN homes out of N homes will be the adopters.

For each home, b_i is defined as how much the home would save on its annual electricity bill if it had a net-zero rooftop solar system, i.e., a system that renewably generates 100% of a home's electrical energy needs over one year. According to Patel et al. (2019), households that consume more power have higher absolute annual savings because they have larger net-zero systems. For the overall adoption rule, the adopters will be the rN homes with the highest values of b_i over all the city, whereas under the even adoption rule, the adopters are the homes that are in the top r within their cluster based on the order of b_i. As a result, the adoption is uniform and equal to r in all clusters under the even rule.

3.2. Data

Patel et al. (2019) also processed building inventory and power consumption data to carry out a study in San Carlos. The building inventory data were obtained based on files from the San Mateo County Tax Assessor, which provides the latitude and longitude coordinates for over 8400 single family homes in San Carlos. In addition, the data also contains the height and the square footage of the homes. We used a Bayesian inference based on building heights to separate single story homes from two story homes. Figure 1 shows the spatial distribution of the households in San Carlos.

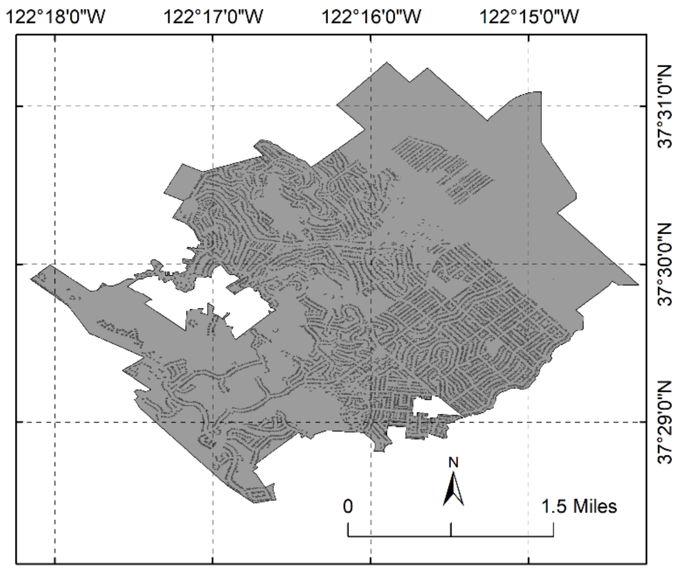


Figure 1 – Single family homes in San Carlos, California, with homes shown in black.

Data on the household's electrical energy consumption was obtained from smart meters for over 1800 single family homes in San Carlos and an additional 46 single family homes in Redwood City, California. The smart meters recorded hourly electrical energy consumption for each home from November 1, 2011 to October 31, 2012. The hourly data were then summed together to obtain the daily energy consumption for each household.

Because the electrical energy consumption data does not provide the specific location of the meters, a precise one-to-one matching between the consumption data and the construction data could not be performed. Therefore, the square footage of each home was correlated with electrical energy consumption with the use of stratified sampling in order to assign meter data to each building.

3.3. Earthquake simulation

Patel et al. (2019) modeled the 1906 magnitude 8.0 San Francisco earthquake to study the effect of catastrophe C on the resilience of DERs. The magnitude and rupture geometry of the earthquake were obtained from OpenSHA software in accordance with Uniform California Earthquake Rupture Forecast (UCERF) version 2 [7], [8]. We computed 500 realizations of average spectral accelerations, Sa_{av} in San Carlos to represent the shaking intensity and assumed that each realization causes a power outage of at least one day. These realizations were estimated using recently developed ground motion and spatial correlation models for Sa_{av} [9], [10].

After an earthquake, buildings are red tagged if they are unsafe to be occupied. To determine the probability of buildings being red tagged, fragility functions developed by Heresi & Miranda (2019) for wooden houses compatible with the intensity measure Sa_{av} were used. Figure 2 shows the likelihood that each household will be red tagged after the earthquake scenario estimated using 500 realizations.

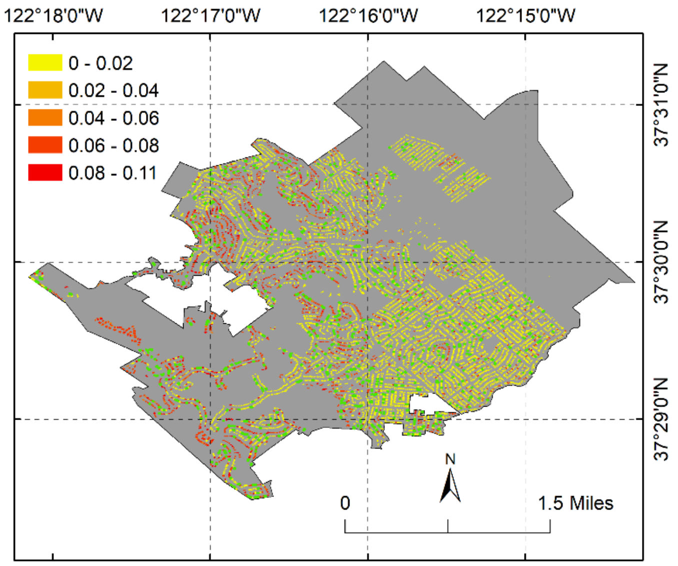


Figure 2 – Likelihood that households are red tagged after the magnitude 8.0 earthquake scenario in San Carlos, California. The households that adopted solar panels are also shown in green.

3.4. Current solar adoption

Existing databases on solar panel adoption are outdated and largely incomplete (e.g., National Renewable Energy Laboratory (NREL) Database, National Solar Database). To address this issue, Yu et al., (2018) utilized computer vision and satellite imagery to estimate high-resolution solar panel adoption in the entire U.S. The estimates are based on a convolutional neural network (CNN) application to identify the locations of solar panels through multiple high-resolution satellite images of San Carlos. In addition, a semi-unsupervised transfer learning model was used to determine the size of the solar panels. A clustering algorithm was also used to identify solar panel arrays, which are a group of solar panels that belong to the same building. Yu et al., (2018)'s results show that in San Carlos 8.5% of the households adopted solar panel arrays.

Because solar panels were mapped at the rooftop level and building footprints were mapped at the ground level using different satellite images, some of the solar panel predictions fell outside the building footprint polygons. To address this discrepancy, we used a modified K-nearest neighbor algorithm with $k = 1$ to match each solar panel array with the closest building. The algorithm was modified to ensure that each building has only one solar panel array. Figure 3 shows the final distribution of the current adoption of solar panels in San Carlos city.

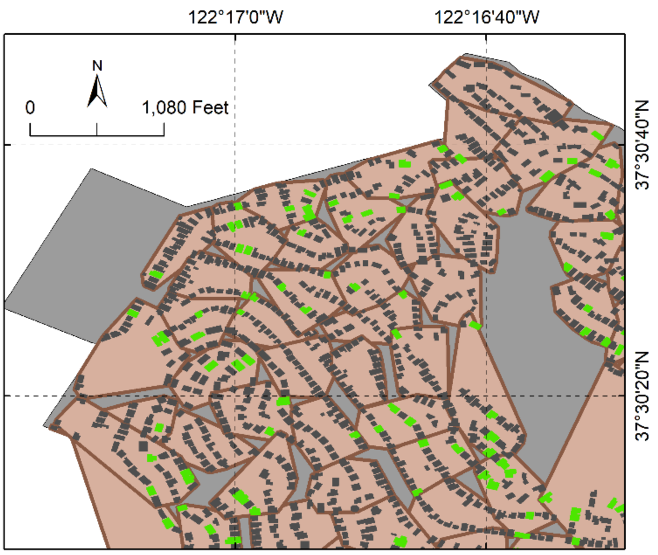


Figure 3 – DERs in San Carlos city. Houses that adopted solar panels are shown in green. Potential microgrids with a size of 20 are shown with brown polygons.

3.5. Solar generation

Total solar energy generation is a function of the solar irradiance conditions and the size of solar panels. We determined the size of the solar panels in San Carlos as net-zero systems. In California, current policy requires the deployment of net-zero energy generation in new buildings [12], which means that buildings will have to generate 100% of their power consumption from renewable sources over a certain time span. Additionally, we modeled global horizontal irradiance (GHI) for San Carlos using a beta distribution that was fitted to historical data collected from weather stations in California that showed hourly-varying solar irradiance [13].

3.6. Microgrids

We modeled microgrids as clusters of residential homes grouped together to share energy and balance their accumulated power loads. We assume that microgrid clusters in San Carlos have similar sizes and that they include residential houses that are geographically close. Accordingly, we used a same-sized k-means algorithm with a Euclidean distance metric based on the houses' geographical coordinates [14]. In a real context, San Carlos might develop microgrid clusters that have different sizes or are based on factors other than geographical proximity. However, because the main goal of this paper is to start quantifying the benefit of microgrids for improved post-earthquake power accessibility rather than capturing potential nuances in microgrid adoption, we consider that the assumptions in the clustering algorithm provide a useful starting point to guide the future deployment of microgrids to improve the resilience of power accessibility.

Patel et al., (2019) tested multiple microgrid cluster sizes within San Carlos and observed that sizes between 20 and 25 provided the most benefit for power accessibility after a magnitude 8.0 earthquake. Thus, in this paper we only show results for a cluster size of 20. Figure 3 shows some of the resulting microgrid clusters in the central-northern part of San Carlos. The plot also shows that given current adoption, these microgrids would have at least a few houses with rooftop solar panels.

4. Guiding policy for power system resilience

The power accessibility of the microgrid clusters were evaluated in time spans $\hat{s}$ of one day within seasonal and annual periods of analysis T. We utilized a load reduction $f = 1/3$ on the pre-earthquake energy consumption to represent that the households would only sustain basic house functions such as refrigeration, heating, and lights at night during the earthquake aftermath.

4.1.Current status

We computed the risk metric for each realization of the 500 earthquake ground motions under different seasons and for the entire year. The risk metric, estimated as shown in Eq. (1), should approach 0 if the solar generation meets the post-earthquake energy needs within clusters. However, our results show that the median risk metric is close to 1 in all seasons. Figure 4 shows box plots on the 500 ground motion realizations for each season and the entire year. The plot indicates that the current 8.5% adoption of rooftop solar is very unlikely to balance the post-earthquake loads in San Carlos and that the post-earthquake power accessibility is worse in the fall and winter seasons as a result of lower solar generation.

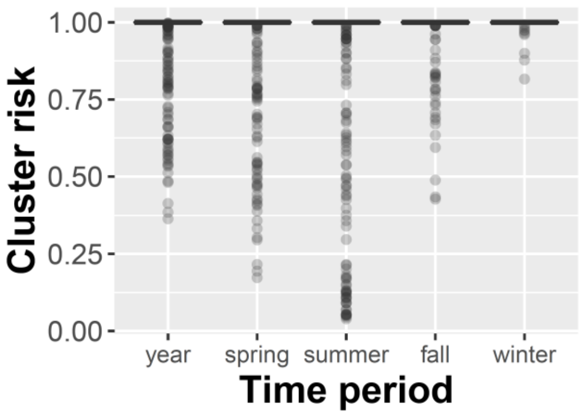
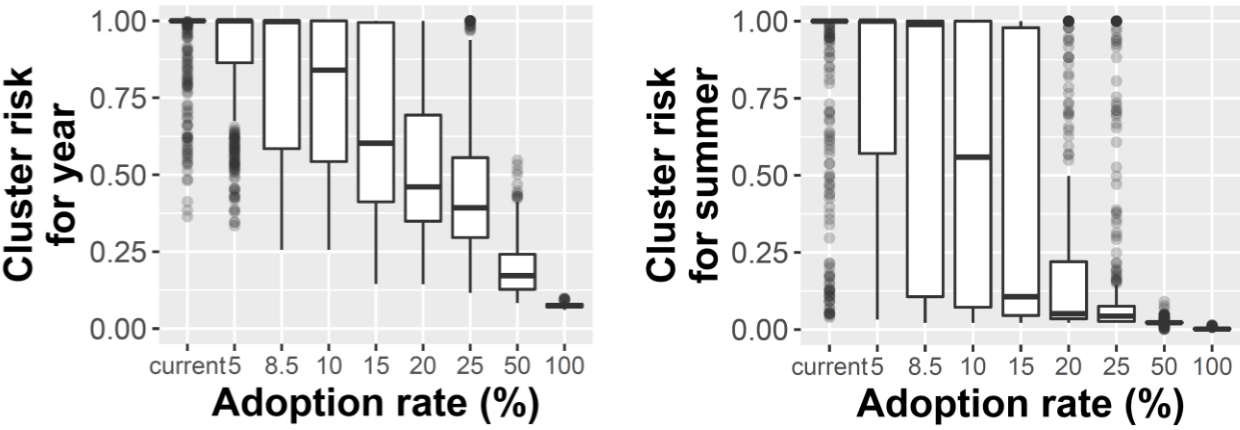


Figure 4 – Seasonal variations of risk metric under current rooftop solar panel adoption.

4.2.Increasing adoption

We also compared the power accessibility gains from current adoption to projections on increasing adoption. First, we utilized the projections under an overall adoption rule. As described earlier, under this rule households that adopt rooftop solar first are the ones that save the most on electricity bills, which for net-zero solar systems are the households with largest power consumption. Patel et al. (2019) estimated the risk metrics under the overall rule for adoptions of 5, 10, 15, 20, 50, and 100% for multiple seasons [5]. We extended this analysis to include an adoption of 8.5%, equal to the existing adoption but under the overall adoption rule. Patel et al. (2019) showed that with 20% adoption the risk metric is 0.5 over the entire year and close to 0 during the summer season. These results indicate that though accessibility would not be as high during the winter or fall seasons, only a 20% adoption would effectively provide power accessibility during the summer to the entire city of San Carlos. Figure 5a and b show box plots with simulated risk metrics for the current and for these projected adoptions during annual and summer periods of analysis, respectively. The comparison shows that for the same number of households with rooftop solar, the risk metric under the current adoption rule performs worse than under the overall rule. In fact, even though currently 8.5% of households in San Carlos have adopted rooftop solar panels, the risk metric performs worse than with lower adoption under the overall rule, e.g., 5%.



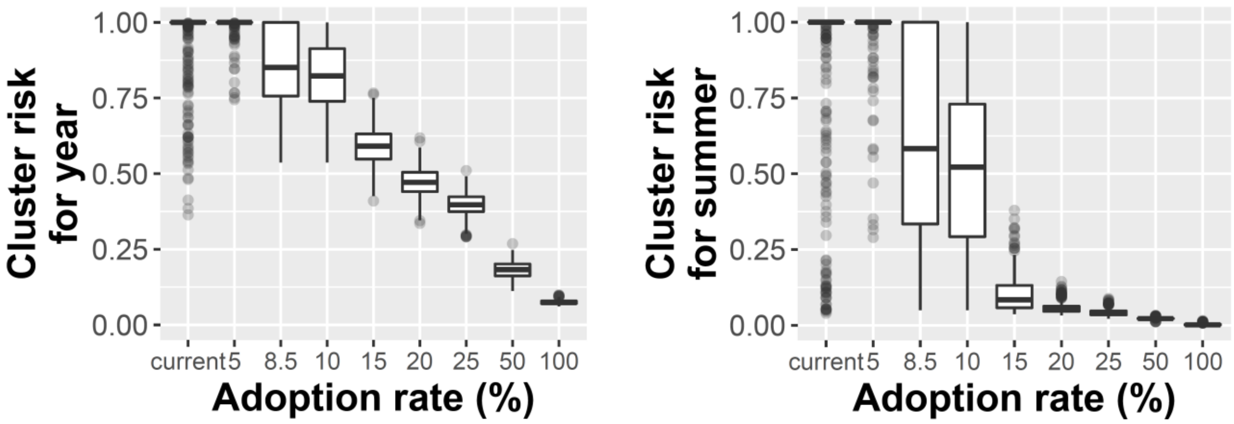
a) Over entire year b) Over summer season

Figure 5 – Risk metric under the overall adoption rule.

The overall rule's higher performance is due the fact that for a given adoption percentage the overall rule represents an upper limit on the cumulative solar panel area over the entire region of analysis. As described earlier, under the overall rule, households that adopt first are the ones that have the largest power consumption and largest net-zero rooftop solar systems. Thus, even with a lower adoption percentage, the power accessibility under overall rule performs better than the power accessibility under the current adoption rule. These results indicate that the current solar adoption is not solely based on bill savings and that other factors, such as socioeconomic traits, environmental awareness or governmental incentives, can play a key role in encouraging solar adoption.

4.3.A more even adoption strategy

We also compare post-disaster power accessibility from the existing adoption to projections on increasing adoption under a more even adoption strategy. Under the even adoption rule, the first households that adopt solar panels are the ones that have the largest bill savings within each microgrid cluster. As a result, the adoption percentage is the same across all the clusters. Patel et al. (2019) estimated the risk metrics under the even rule for adoptions of 5, 10, 15, 20, 50, and 100% for multiple seasons [5]. We also extended this analysis to include an adoption of 8.5%. Figure 6a and b show box plots with the simulated risk metrics for the current and for these projected adoptions during annual and summer periods of analysis.



a) Over entire year b) Over summer season

Figure 6 – Risk metric under the even adoption rule.

These results show that the median risk metric is practically the same as the median found under the overall adoption rule. However, the risk metric variance under the even rule is significantly smaller than under the overall rule. Each risk metric sample is a measure that combines the ability of all microgrid clusters to meet their respective post-earthquake power needs under different realizations of earthquake ground motion. Because the even rule does not significantly modify the aggregated solar generation capacity with respect to the overall rule, but strongly modifies its distribution across different clusters, the median risk metric barely changes. However, the variability in the ground motions triggers more extreme cases under the overall rule because solar adoption in microgrid clusters is not uniformly distributed. In this case, microgrids with low adoption will rely on the survival of the very few households that adopted solar panels, and thus these microgrids will have a reduced likelihood of meeting their post-earthquake power needs.

5. Conclusions

This paper presents an analysis of the increase in post-disaster power availability in San Carlos, California, introduced by the adoption of rooftop solar panels in households. Because traditional power systems often have massive failures after extreme natural disasters, the current rapid adoption of DERs and the potential large-scale deployment of microgrids can effectively increase the resilience of power system to natural disasters. This paper provides a quantitative evaluation of such an increase in resilience for earthquake hazards comparing current percentages of solar adoption to projected percentages.

This paper summarized a quantitative methodology that merges earthquake analytics and energy generation models of rooftop solar panels to evaluate post-earthquake power accessibility in clustered households. The methodology captures different seasonal effects that have direct impact on the generation capacity of households. Additionally, the methodology represents microgrid behavior by defining a risk metric that measures the ability of clusters to cooperate and share energy in case of a main grid outage.

We utilized computer vision high-resolution estimations on solar panel adoption to evaluate the power accessibility in San Carlos after a magnitude 8.0 earthquake. We also evaluated the increase in the power accessibility stemming from the projected adoption growth of rooftop solar panels. Our results also show that microgrids can be effective in redistributing energy generation and meeting post-earthquake power needs. During the summer, only 20% adoption can be effective for providing enough generation to meet post-earthquake power needs in San Carlos. However, the city's existing adoption of 8.5% is insufficient to meet its power needs in the aftermath of the magnitude 8.0 earthquake.

We also showed that post-disaster power accessibility strongly depends on which households adopt solar and where they are. In net-zero rooftop solar systems, households with high energy consumption will have larger solar generation capacity. Thus, if they are the first households that adopt solar within a city, then the accumulated generation capacity is maximized within the city. Even though households that have higher power consumption have higher electric bill savings, a comparison with the current adoption suggests that in practice, adoption does not fully depend on electric bill savings. As a result, San Carlos has lower post-earthquake power availability than if adoption had been fully based on bill savings. Finally, we also showed that if solar adoption is uniformly distributed across the microgrid cluster, the overall median power accessibility barely changes. However, the variability of this post-earthquake accessibility decreases significantly as a result of a more even distribution of risk across microgrids.

6. Acknowledgements

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5. Copyrights

7. References

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