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Enhancing equitable resilience of urban energy systems via strategic planning of EV charging infrastructure

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ABSTRACT

This paper seeks to address the profound power resilience inequity in New York City by means of strategic allocation of electric vehicle (EV) charging infrastructure to support the power grid operation in challenging scenarios, such as when facing high demand or during natural disasters. First, we uncover the most disproportionately affected communities in New York by developing a metric of power resilience inequity to measure the combined impact of power failure-related factors on these areas. We employ data-driven approaches to infer the statistical relationships between communities' power resilience index, their available EV charging infrastructure, and several other prominent socio-demographical variables. This inference yields the development of a machine learning model that can predict the reduction of power resilience inequity after deployment of the proposed resource allocation strategy. We further develop an optimization framework that jointly considers equity and efficiency to guide the optimized distribution of EV charging infrastructure across the city. A number of case studies are leveraged to demonstrate the capability of the devised approach in enhancing urban power resilience equity, yielding favorable results in marginalized communities.

1. Introduction

1.1. Power resilience in New York City

Power systems resilience refers to the recurring ability of a power system to anticipate, survive, sustain, recover from, and adapt to high-impact low-frequency events. These events include natural disasters as well as man-made disasters (Chattopadhyay and Panteli, 2022; Raoufi et al., 2020). As climate change continues to cause an increase in the frequency of natural disasters, there is more widespread worry about the effects of a greater number of heatwaves and storms globally; thus the topic has garnered attention from researchers worldwide. Related works have explored several means of boosting power resilience, such as line hardening and supplemental power sources in an effort to mitigate power failure in rural areas, congested cities, and suburbia in between. There is also growing concern surrounding the impact of increased disaster frequency on the power grid in New York City (NYC), especially in the wake of Hurricanes Isaias and Ida in 2020 and 2021. Power grid failures affect some city regions disproportionately based on factors such as electric infrastructure efficiency and proximity to the shoreline.

NYC's power generation plants are local. Many are located along the waterfront of Queens, making them more susceptible to interference during periods of severe weather (NYC Planning, 2020). For example, during heat waves, the less efficient plants are unable to keep up with the surge in demand for electricity, and blackouts become more likely. To plan ahead for neighborhoods along the shoreline, the City has launched the Resilient Neighborhoods initiative to support the power resiliency of the communities in the floodplain (NYC Planning, 2020). In July 2022, the New York Power Authority (NYPA) announced that it has been named a co-founder of the global initiative Climate READi, which aims to create a more resilient power system by developing a common framework for the design of future resilient energy systems (NY Power Authority, 2022).

But, as a shift toward renewable energy sources also looms, enhancing power resilience may become more complex. New York's Climate Leadership and Community Protection Act (CLCPA) requires 70% of the state's energy from renewable sources by 2030, but greater reliance on sources like wind and solar power presents the challenge of system reliability. Wind lulls, for example, can greatly influence power generation, and solar power will not be able to contribute sufficiently to

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forecasted evening energy peaks in the winter months. The CLCPA also set a goal of an 85% reduction in economy-wide greenhouse gas emissions by 2050, which will require significant investment in electric building heat and electric vehicles (EVs), increasing the amount of power needed across the state (New York ISO, 2020).

1.2. Electric vehicle use and infrastructure utility

According to state data, around 21,000 EVs are registered in New York City, which is less than 1% of all the city's registered vehicles. Currently, factors like negative perceptions about EVs, high retail prices due to increasing demand, and inconsistent access to EV charging stations have caused many consumers not to consider purchasing them. The borough with the most registered EVs is Brooklyn with over 10,000, followed by Manhattan and Queens, both with approximately 3900 (Gothamists, 2022). Yet, the vast majority of EV charging stations are located on Manhattan Island. Though most electric car owners charge their cars at home or work, ownership is more difficult for consumers who cannot. Many New Yorkers live in apartment buildings without access to chargers, and getting access to alternative charging stations is especially difficult in the Bronx, Queens, and Staten Island, where there are very few public stations.

Portable power batteries are a promising technology already being utilized by EV owners. ZipCharge's Go, for example, is a power bank about the size of a carry-on suitcase that can provide between 20 and 40 miles of range on any electric or hybrid plug-in vehicle. These devices can be used as power sources in emergency situations which could play a role in enhancing urban grid resilience (Dugan et al., 2021; Hussain and Musilek, 2022; Forbes, 2022). An increase in registered EVs may bring a great benefit to New Yorkers in the renewable future as battery sources can help pick up the slack of wind and solar sources in times of high demand, which would improve resiliency in disproportionately affected areas of NYC. Vehicle-to-Grid (V2G) technology allows energy to return to the power grid from the battery of an electric car. Similar technologies are Vehicle-to-Home and Vehicle-to-Load, which can be used to power appliances (ABB, 2020; Gothamists, 2022). The benefit of these technologies in times of urgent need highlights the importance and positive influence of equitably-allocated EV charging infrastructure which promotes equitable energy resilience.

1.3. Equitable power resilience

"Equity" is distinguished from "equality" in that it refers to fairness and justice in the context of societal imbalances that require individuals with a greater need to have access to a greater portion of resources allocated. Energy equity (Barlow et al., 2022) has received significant attention, including investigations on the access to distributed energy resources (Brockway et al., 2021), utility regulation (Farley et al., 2021), outage durations (Liévanos and Horne, 2017), energy storage (McNamara et al., 2022), and energy usage (Tong et al., 2021). Power grid resilience also needs to consider equity in its planning process. Some specific resilience measures include resource allocation such as power backups and agile outage restoration plans in distinct communities (Lin et al., 2022). In this work, we utilize EVs as a means to enhance urban grid resilience which can be enabled by V2G technologies (Brown and Soni, 2019; Hussain and Musilek, 2022; Simental et al., 2021). Thus, equitable public EV charger distribution would facilitate improvements in power resilience in the neighborhoods that need it most. In these areas, the availability of electric chargers will incentivize residents to purchase an EV, which in turn will make V2G technology more useful as more EVs begin to circulate in the city. This will also cause an eventual uptick in portable charger purchases, which can further support the power grid in times of need.

The main objective of this work is to design a mathematical framework for the optimal allocation of EV charging resources to achieve equitable power systems resilience in New York City. Thus, a thorough investigation of power grid stress and EV charging infrastructure in different communities across NYC is necessary. To this end, data-driven approaches are leveraged to quantitatively assess the disproportionate distribution of EV charging infrastructure and power outage impacts on residents in different regions of the city. The equitable distribution of public EV charging infrastructure is vital to achieving equitable resilience of urban energy systems per the evidence that EV adoption increases with greater charging infrastructure accessibility (Mersky et al., 2016; Kumar et al., 2021), and that EVs can be maturely and conveniently integrated with the power network through V2G and similar technologies (Hussain and Musilek, 2022; Rahimi and Davoudi, 2018).

1.4. Related works

Related works consist of those which propose different methods to solve an issue similar to that posed by power failure, or which propose similar methods to solve a similar issue. For example, the authors in (Ghasemi et al., 2021) also propose the development of an optimization framework for resilient distribution system planning, making use of facilities such as line hardening to strengthen the power network. This framework considers trade-offs between the economic value of resources under normal systems operation and the value of their enhancement of network resilience. It does not assess the impact of the individual line-strengthening techniques used. Similarly, the authors in Xu et al. (2020) use a simulation-based optimization approach to minimize the cost of cascading outages, more specifically.

The work established in Mahzarnia et al. (2020) reviews the most widely used approaches to strengthen power resilience, and in Abiodun et al. (2022) the authors assess the effectiveness of microgrids in providing support to power grids in rural areas. The authors in Ma et al. (2012) describe a model where EV storage systems are integrated with a power system, and then develop a decision-making strategy for deploying these resources to support the grid.

While all aforementioned works do not consider equity in deploying their strengthening facilities to boost power resilience, in Lin et al. (2022) the authors propose a more general, holistic framework promoting equity in power resilience planning. However, this framework is not tested and there are no quantifiable results to assess it.

This study establishes the inequity in power resilience faced by NYC communities and proposes the utilization of V2G technology to integrate EV chargers with the grid in order to mitigate this. The work will quantify both the inequity faced and the impact of the proposed optimization framework to properly assess its usefulness after the distribution of EV resources. Thus, it is unique in its prioritization of the equity objective in formulating the mathematical framework.

1.5. Organization of the paper

The rest of the paper is organized as follows. Section 2 first develops a metric to quantify power resilience inequity and then systematically uncovers this inequity in NYC by data-driven analysis. Section 3 establishes a metric for evaluating available EV charging infrastructure and reveals its current inequitable distribution across the city. Section 4 develops a mathematical framework to inform the optimized allocation of resources to enhance equitable power resiliency. Section 5 uses case studies to demonstrate the effectiveness of our proposed scheme.

2. Data-driven analysis of inequitable power resilience

2.1. Equitable power resilience indicator

To determine how to allocate EV charging resources equitably across the city, we must first discover which neighborhoods suffer most during natural disasters or times of high power demand. Two factors are paramount in making this discovery: *power outage frequency* and *average recovery time*, or the time it takes for power to be restored on average for a particular neighborhood or ZIP code.

To this end, the Power Outage Complaints dataset[2] is sourced from NYC open data, which contains 44.6k rows of 311 Service Request records from 2010 to present and is updated daily. The data set includes the open and close dates of the complaint ticket, the location of the power outage, and various other descriptive fields. To calculate the power outage frequency, we can count the number of records for each ZIP code, which can be converted to outages per 1000 residents by dividing by the total population in that ZIP with appropriate scale. The population dataset[3] is obtained from US Census Bureau data. The average recovery time (power outage duration) for each ZIP can be directly obtained based on the information on `Created Date` and `Closed Date` of each incident in the dataset.

An indicator of power resilience inequity must be developed in order to investigate the combined effect of recovery time and outage frequency. We denote by T_i and O_i the average recovery time and outage frequency by population for ZIP code $i \in \mathscr{N} := \{1, 2, \ldots, N\}$, where N is the total number of ZIPs of interest. Then, the power resilience inequity metric for ZIP code i is therefore defined as:

$$R_i = \alpha_1 T_i + \alpha_2 O_i, \qquad (1)$$

where $\alpha_1, \alpha_2 \geq 0$ are weighting factors with $\alpha_1 + \alpha_2 = 1$.

A large R_i indicates that the area suffers from a larger degree of power resilience inequity, as it experiences a higher average outage frequency and duration. These areas will appear in red on the heat maps developed based on calculated R_i values.

2.2. Power resilience equity results

2.2.1. Existence of resilience inequity

Fig. 1 shows the distributions of power outage frequency and recovery time in the city. It is observed that T_i and O_i can be significantly different for distinct neighborhoods. For example, the outage frequency is much higher in the Bronx and Central Brooklyn. To further understand the degree of power resiliency inequity faced by communities, we leverage the proposed metric (1), and the result is shown in Fig. 2. The finding indicates that the most disproportionately affected areas in the region are the Bronx and Central Brooklyn.

2.2.2. Persistence of resilience inequity

However, based on the number and nature of natural disasters that occurred over the course of each year, R_i visualizations may appear different as storms or heat waves may affect areas differently, as shown in Fig. 3. Regardless, trends can still be observed in annual visualizations of R_i in recent years—particularly prior to the COVID-19 pandemic—and the inequity observed is *persistent*. Similarly, by filtering dates to include only short periods of time, one can observe the effects of specific disasters on NYC communities in the short term, which helps to expose inequitable power resilience under circumstances where power is most needed. Fig. 4 depicts how severe hurricanes caused disproportionate damages to neighborhoods, and it exposed the structural power resiliency inequity in the urban area.

To learn more about the communities that suffer the most from power resilience inequity and uncover important relationships, we next conduct an analysis of the correlation between NYC resident demographics and the scale of power resilience inequity in their communities.

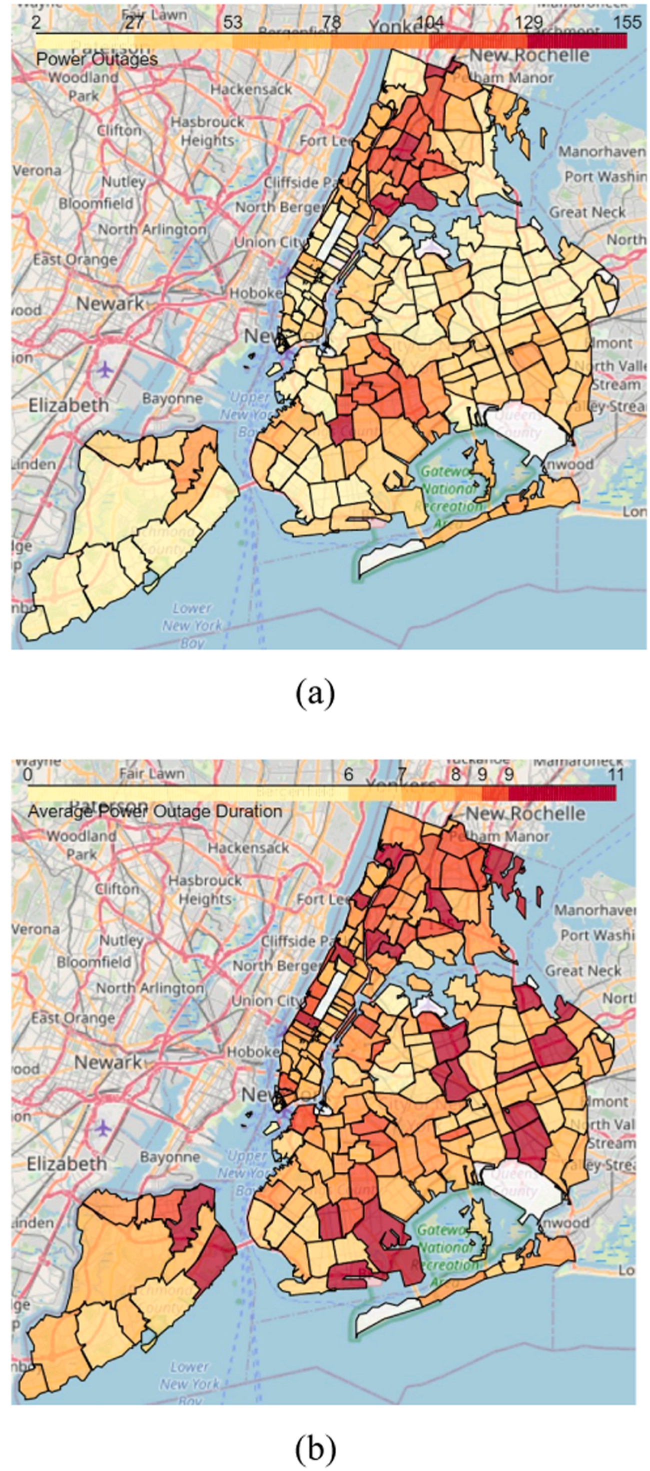


Fig. 1. (a): NYC heat map of outages per 10,000 residents (since 2010) for each ZIP, or O_i. (b): NYC heat map of average outage duration (since 2010) for each ZIP, or T_i. A clear pattern can be seen for outage frequency, which is higher in the Bronx and Central Brooklyn. Though long durations are less concentrated in one area, these communities are still affected by relatively long outage durations.

2.3. Social-demographic correlation analysis

For the purposes of this analysis, we can observe the relationships that both income and ethnic background may have with the level of power resilience in a given neighborhood. This is important to establish

[2] https://data.cityofnewyork.us/Social-Services/power-outage-complaints/br6j-yp22

[3] https://www.newyork-demographics.com

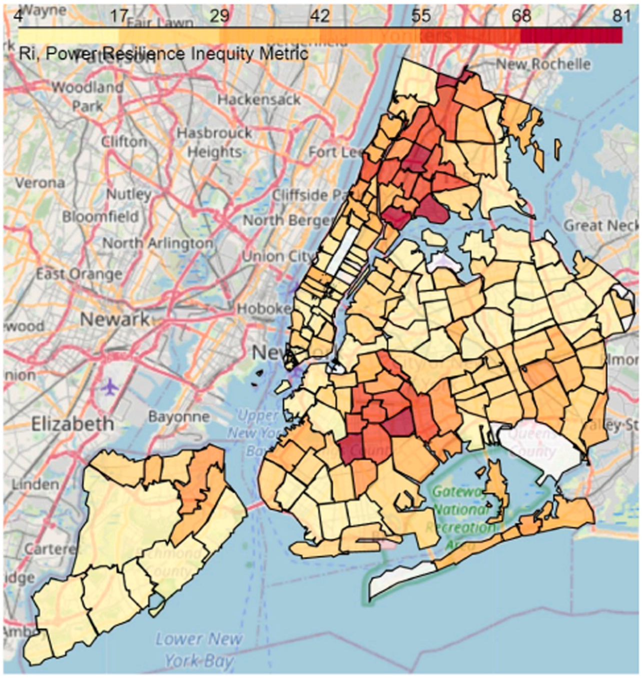


Fig. 2. Map of R_i for each ZIP code where α_1 and $\alpha_2 = 0.5$, using the all-time data from the Power Outage Complaints dataset (2010-Present). As the range of O_i is larger than that of T_i, O_i may have a larger influence over R_i in regions that appear to suffer most from power resilience inequity.

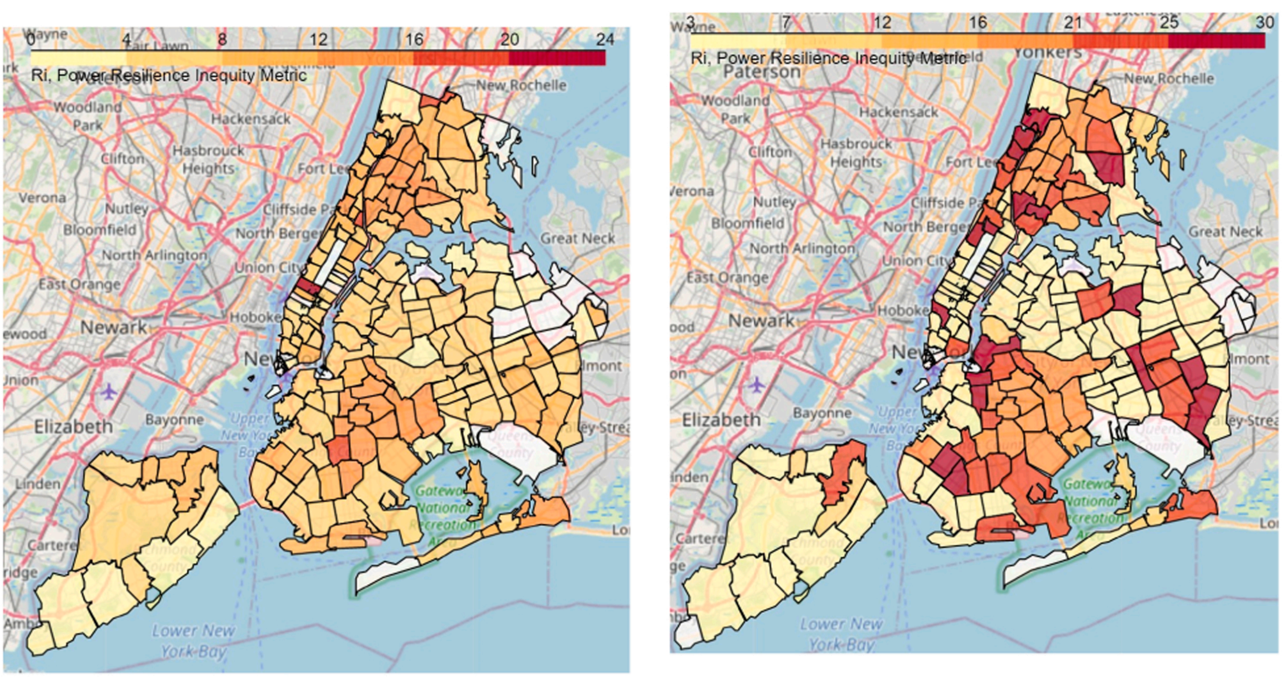
The demographics dataset provides the racial proportion breakdown of residents by ZIP code and is sourced from City-Data,[4] which develops comprehensive reports on individual NYC ZIP codes, compiling data from both government and private sources.

Fig. 5(a) shows that the highest concentration of lower-income households are located in Brooklyn and the Bronx, with most of these households earning less than \$40,000 annually. In contrast, Manhattan has the highest concentration of high-income households, some ZIPs earning an average of approximately \$110,000 a year. The map highlighting communities of color in dark purple and the maps in Fig. 6 show high concentrations of residents belonging to minority groups in similar areas. Both maps correlate strongly with the map of power resilience inequity based on outage frequency and duration.

2.4. Needs for equitable power resilience

The findings in Section 2.3 are troubling on multiple fronts. As we recognize the correlation between less privileged neighborhoods and high power resilience inequity, it is important to note that low-income communities generally have higher energy cost burdens. This may be attributed in some ways to the use of older and less efficient appliances at home that require more electricity, in conjunction with older homes with insufficient insulation (THE HILL, 2021).

Earth's Future is a journal published in 2021 that broke down the socioeconomic and racial correlations with extreme heat in certain communities, both using census data and measuring the land's surface temperature with satellite imaging. The study found that temperatures can be as much as 7 degrees higher in impoverished neighborhoods and communities of color compared to their wealthy and white counterparts



(a) (b)

Fig. 3. (a): R_i for each ZIP in 2016. Tropical storms Bonnie and Hurricane Matthew hit New York this year. The areas with the highest R_i are primarily in the Bronx and Central Brooklyn. (b): R_i in 2018. In this year, tropical storms Gordon and Hurricane Michael hit New York. This map also displays a cluster of high R_is concentrated in South Queens. More dramatic differences in R_i can be observed between ZIPs in this time frame.

how inequity affects different demographics and create a foundation for the regression model to be developed. Heat maps were developed first to better visualize regional patterns, and then these demographic variables were plotted against outage frequency.

due to higher population density, high building concentration, and a

[4] http://www.city-data.com/city/New-York-New-York.html

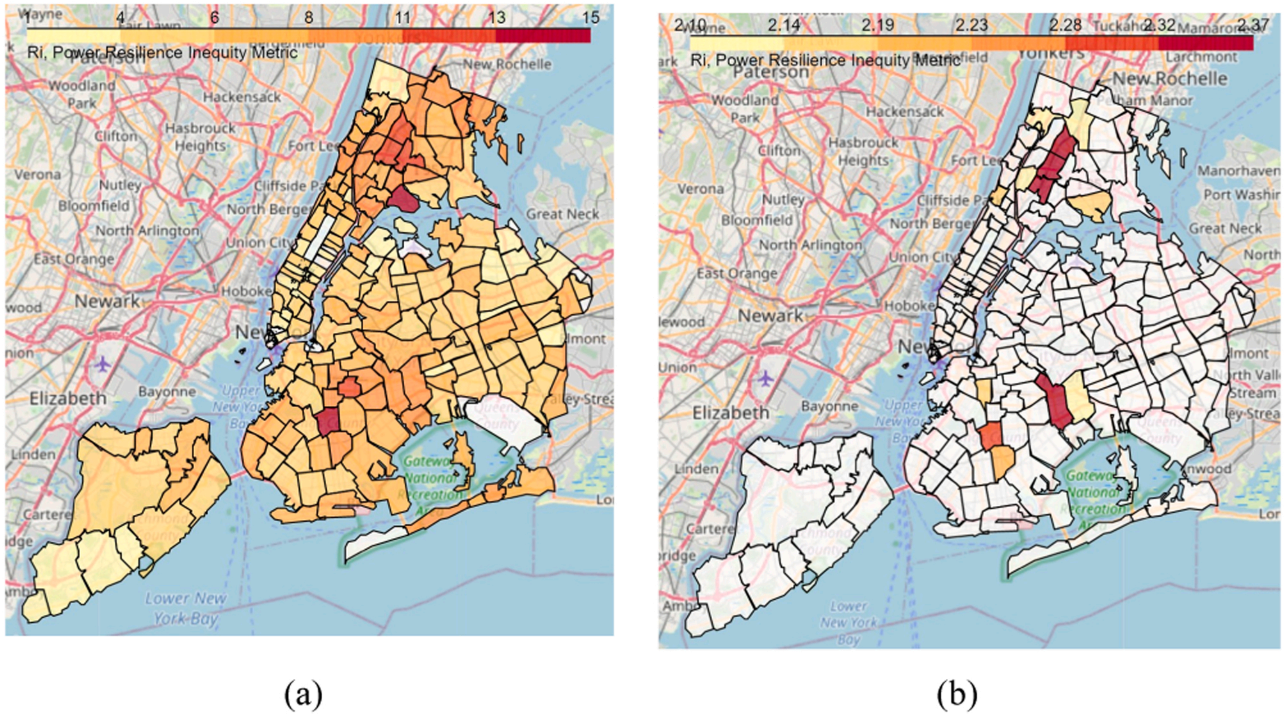


Fig. 4. (a): R_i in 2021, as Hurricane Ida and five other storms hit the region. (b): R_i during Hurricane Ida only, during which power outages were concentrated in Central Brooklyn and the Bronx.

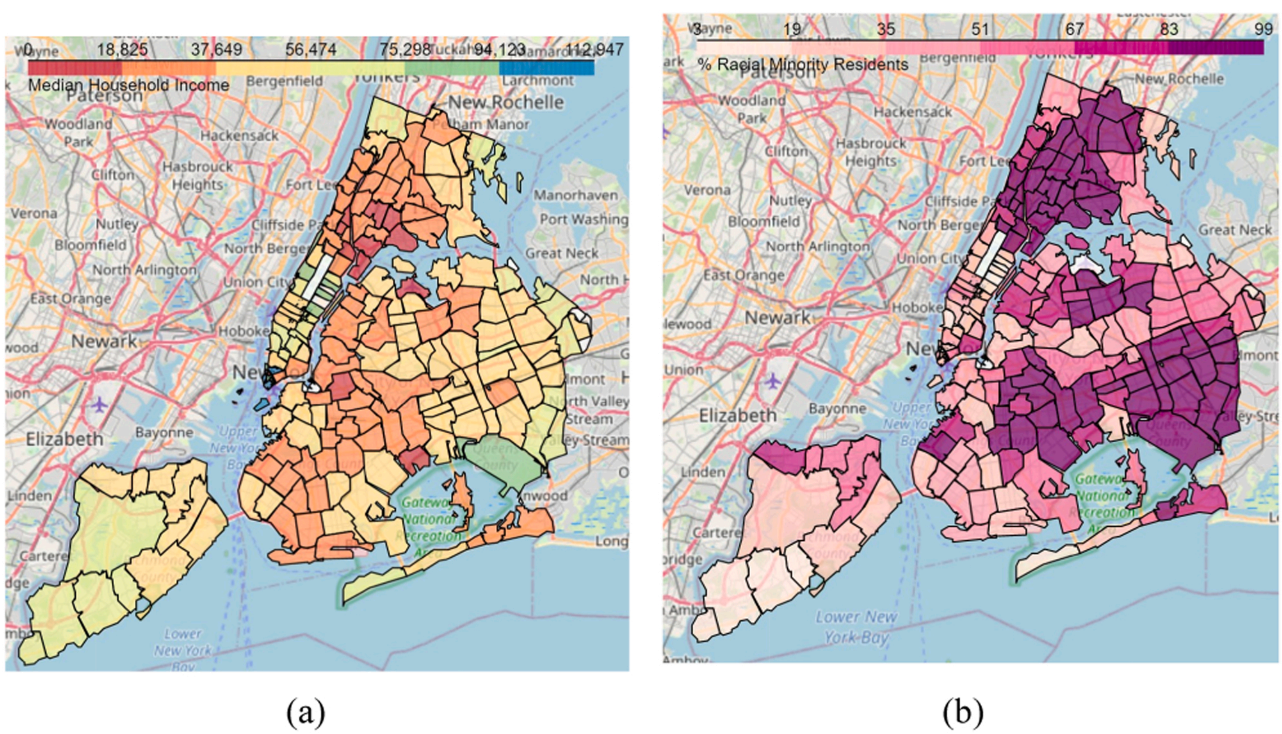


Fig. 5. (a): Map of the median household income in each ZIP code. (b): Map of the percentage of residents belonging to minority racial groups in each ZIP, including Black, Hispanic or Latino, Asian, Hawaiian or Pacific Islander, Indigenous, or mixed race residents.

lack of tree cover. This means that as global temperatures rise, these neighborhoods will be even more susceptible to outages and will continue to pay more for power that is more likely to go out and stay out, unless changes are made accordingly to support power resilience in these areas. This also means that these communities are at a higher risk for heat stress-related injuries (NPR, 2021).

From Fig. 7, we can observe that the percentage of residents belonging to minority groups has a direct positive relationship with outage frequency, and therefore R_i, whereas income has an indirect relationship with frequency. These variables play an important role in

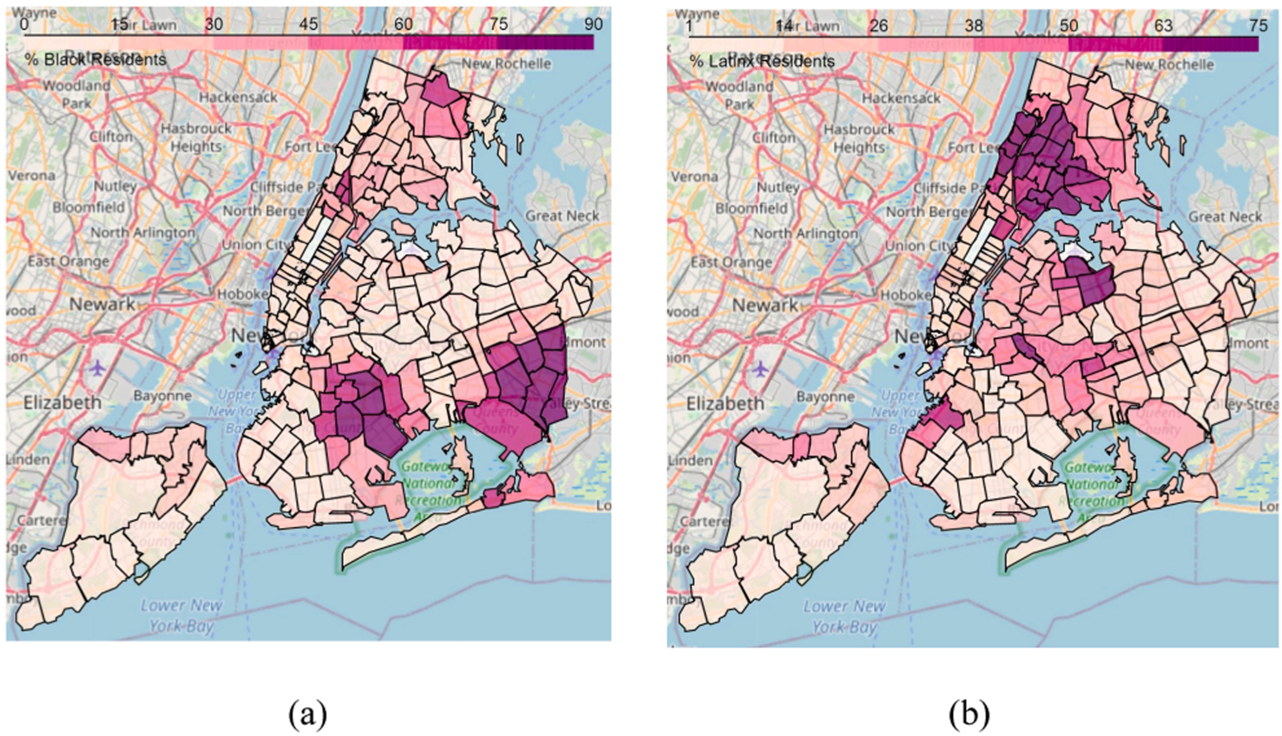


Fig. 6. (a): Map of the percentage of residents in each ZIP code that are Black. (b): Map of the percentage of residents that are Hispanic or Latino. Standing out on the maps in dark pink and purple, the highest values for R_i correlate with these communities most.

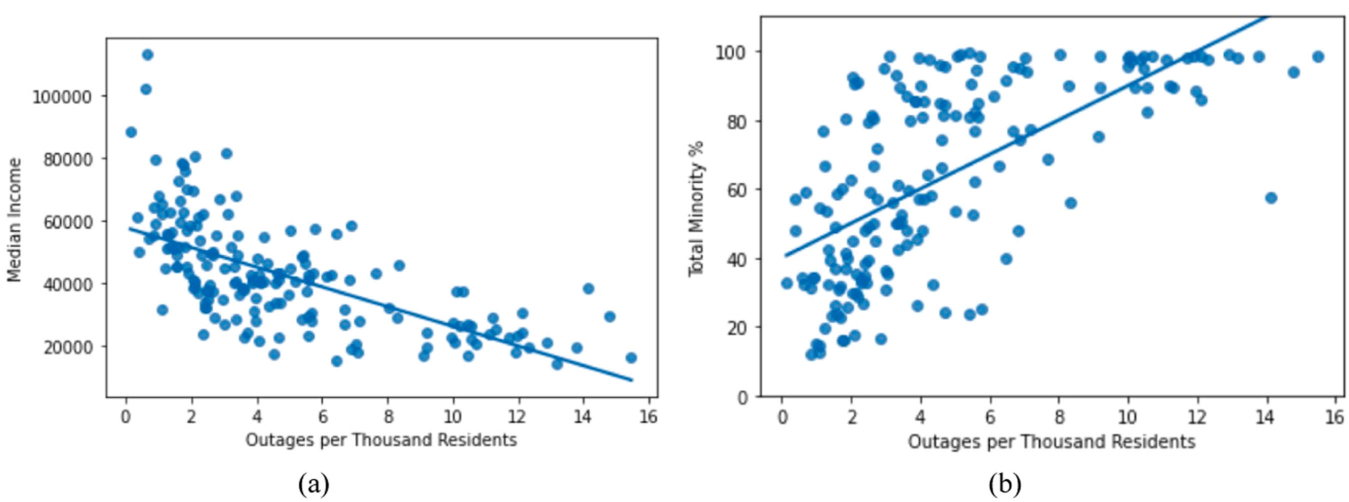


Fig. 7. (a) and (b) show each ZIP's outages per thousand residents against the median income and percentage of residents that are a part of a minority racial group in that location, respectively.

identifying neighborhoods with the most power resilience inequity across the boroughs.

3. Data-driven analysis of inequitable access to EV charging infrastructure

There currently exists a distribution of EV charging infrastructure disproportional to demand as based on population and EV prevalence in some NYC neighborhoods. In leveraging data, we quantify the inequitable availability of public resources and make connections to active socioeconomic factors.

3.1. Distribution of EV charging infrastructure

An analysis of the current distribution of EV charging infrastructure is a necessary step before further resources can be allocated equitably. The Alternative Fuel Stations dataset[5] is sourced from the U.S. Department of Energy's Alternative Fuel Data Center, which provides a list of all EV charging stations in the United States as of June 2022. It includes the address of the station, access limitations, open date, and more.

The dataset is cross-referenced to a list of all ZIP codes in the 5 boroughs in order to filter by location. A new data frame was arranged

[5] https://afdc.energy.gov/stations/#/find/nearest

including each NYC ZIP code's respective number of EV charging stations. Denote by $E_i, i \in \mathcal{N}$, the indicator of access to EV charging infrastructure of residents in ZIP code i. Here, E_i can be quantified according to

$$E_i = \frac{NE_i}{P_i}, \tag{2}$$

where NE_i and P_i are the number of EV charging stations and the population density in ZIP code i, respectively.

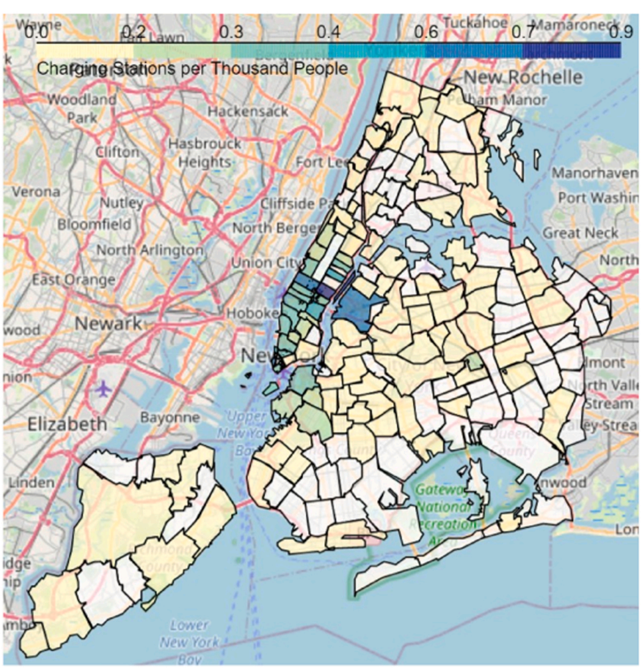
In order to find the amount of charging stations per 1000 people in each location, a population data set was leveraged to divide the count of EV stations by the corresponding population in each ZIP. The amount of EV charging stations per 1000 residents is acquired by multiplying the quotient by 1000 and then mapped to uncover the distribution of EV charging infrastructure in the city.

3.2. Social-demographic correlation analysis

Analysis of the demographics with the worst access to EV charging infrastructure is also necessary before allocating additional resources, and can also strengthen correlations uncovered previously in Section 2.3.

Fig. 8 illustrates that most ZIP codes without any EV charging infrastructure are in Brooklyn, the Bronx, and Queens. As discussed previously, these areas also have a higher percentage of residents belonging to minority racial groups. This pattern can also be observed when comparing the ZIP code's racial makeup and available EV charging infrastructure directly.

The results shown in Figs. 9 and 10 demonstrate the relationships between the availability of public EV charging infrastructure and demographic factors, which are similar to those observed in the context of power resilience inequity. Low-income communities and communities of color can be seen to have poorer access to the resources they need during power emergencies. Therefore, an equitable allocation of these EV charging resources is imperative to mitigate the infrastructure access inequity.



(a)

Fig. 8. The distribution of the number of EV chargers available per 1000 people in the five boroughs in NYC. Areas that are displayed in white have no publicly available EV charging infrastructure. The area with ZIP 11430 is disregarded. Note: The high concentration of EV charging infrastructure in this ZIP, due to the presence of JFK International Airport, skews results as we look at the effects of infrastructure on power resilience.

4. Mathematical formulation for equitable power resilience planning

The ultimate goal of this study is to achieve equitable power systems resilience by designing a strategic roll-out plan for EV charging infrastructure by allocating these resources to areas where they will make the most positive impact.

4.1. Inference on power resilience and its cofactors

Before formulating the problem that informs optimal decision-making, we need to identify the relationship between the EV charging infrastructure and equitable resilience. A larger E_i indicates that there are more readily available resources for emergent power recovery in ZIP code i when facing disasters. Furthermore, E_i can be regarded as an approximate indicator of how well-developed the critical infrastructure is in the corresponding neighborhood and thus impacts the power outage frequency O_i. Therefore, E_i can have a direct impact on the recovery time T_i and power outage likelihood and henceforth the resilience inequity measure R_i. We leverage a linear model to uncover such a relationship. Specifically, the constructed linear regression model admits the following structure:

$$R_i = \beta_0 + \beta_1 E_i + \beta_2 D_i + \beta_3 I_i, \tag{3}$$

where D_i and I_i denote the percentage of non-white-identifying population and average median income of residents in ZIP code i, respectively. β_0, β_1, β_2, and β_3 are coefficients to be learned from the data.

The linear regression model assumes that there exists a linear relationship between predictor variables and the outcome variable, and that there is no multicollinearity between predictor variables. To verify this, the variance inflation factor (VIF) was calculated for predictor variables and the resulting values were all below the threshold of 10, with the highest value at only 4.3.

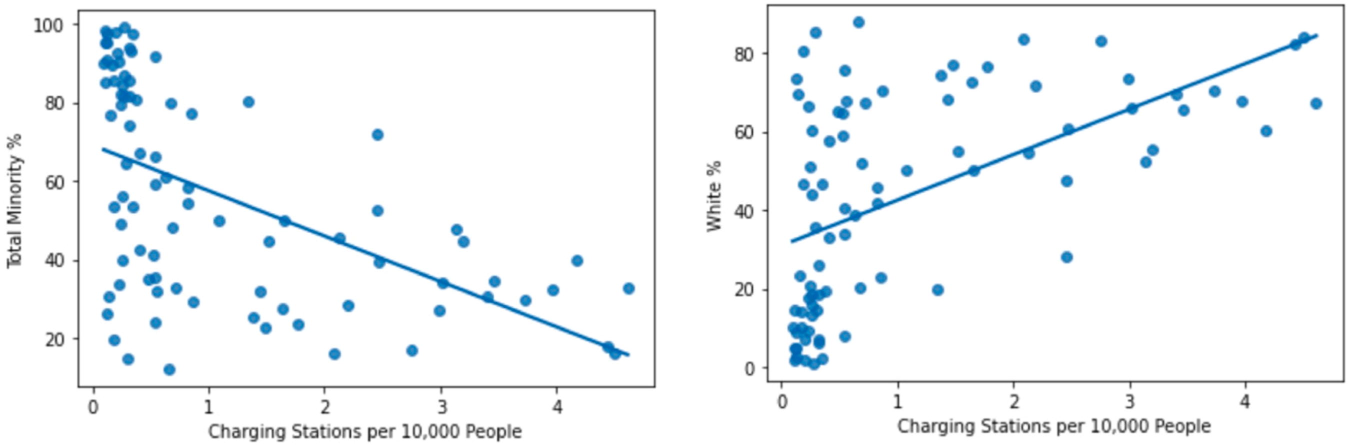
Linear regression is based on gradient descent training to find coefficient values that minimize the error between actual and predicted values. The algorithm will recompute the coefficient values based on the gradient until it converges to a minimum. The complexity of such an algorithm depends on the size of the dataset and the number of features used as predictors, which admits $O(kN^2)$, where k is the number of features and N is the number of data points. With less than 200 ZIP codes in NYC and 3 predictor variables, the algorithmic complexity will be relatively low in this study, i.e., $O(N^2)$.

4.2. Mathematical problem

Other than equitable resiliency, the framework developed should consider trade-offs between equity and efficiency, where in this context, the efficiency aligns with the demand across NYC for EV charging infrastructure.

Denote by $x_i \geq 0$ the planning decision of additional EV charging resources (such as charging ports, station) allocated to ZIP code i. For computational convenience, we do not restrict x_i to taking an integer value. A decimal solution of x_i can be interpreted as the EV charging infrastructure capacity. However, one can further round the obtained planning decision to the feasible integer solution through approximation. Then, $\widetilde{E}_i$ below captures the average charging resources available to residents in ZIP code i after the addition of EV charging infrastructure:

$$\widetilde{E}_i = E_i + \frac{x_i}{P_i}.$$



(a) (b)

Fig. 9. (a) and (b) show the correlation of each ZIP's available charging infrastructure, EVs per 10,000 residents, against the total percent of residents belonging to minority groups and the percentage of residents that are white, respectively.

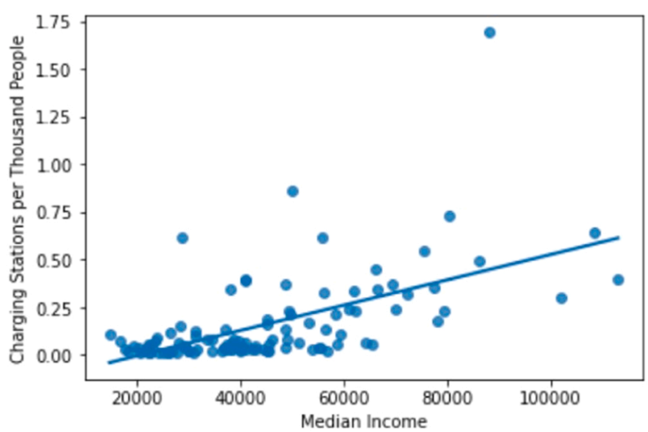


Fig. 10. Correlation of the income against the EV charging stations available to the public in each ZIP code.

An increase of E decreases T and O and thus lowers the degree of resilience inequity $\widetilde{R}$. Based on (3), $\widetilde{R}$ can be directly quantified as follows:

$$\widetilde{R}_i = \beta_0 + \beta_1 \widetilde{E}_i + \beta_2 D_i + \beta_3 I_i. \tag{4}$$

Given a budget of $B \geq 0$ EV charging infrastructure resources, the city government needs to decide how to allocate them efficiently to satisfy the charging needs while considering its contribution to equitable power resilience such as under disaster recovery circumstances. The efficiency in the objective captures the heterogeneous demands of EV charger usage across neighborhoods. The new installation plan should align with this statistical fact. To this end, denote by

$$\rho_x = \left[\frac{NE_i + x_i}{B + \sum_{i\in\mathscr{N}} NE_i}\right]_{i\in\mathscr{N}} \tag{5}$$

the new distribution of EV charging infrastructure in the city based on the planning decision $x_i, i \in \mathscr{N}$. The demand distribution for EV chargers in the city is denoted by ρ_d, which can be inferred from the historical data. Then, it is desirable to have distributions ρ_x and ρ_d close to increase utilization of the charging infrastructure. The equity objective ensures that residents in different areas have no significant disparity in terms of power energy resilience. Therefore, an effective and equitable EV infrastructure decision-making plan can be obtained by solving the following optimization problem:

$$\begin{aligned} &\max_{x_i, i\in\mathscr{N}} -KL(\rho_x||\rho_d) + \sum_{i\in\mathscr{N}} \eta_i \log(\widetilde{R}_i + 1) \\ &\text{s.t.} \sum_{i\in\mathscr{N}} x_i = B, \\ &x_i \geq 0, \quad \forall i \in \mathscr{N}, \end{aligned} \tag{6}$$

where $KL(\cdot||\cdot)$ denotes the Kullback-Leibler (KL) divergence measuring the difference between two discrete probability distributions; $\eta_i > 0$ is a weighting constant between efficiency and equitable resiliency. Note that $\eta_i \log(\widetilde{R}_i + 1)$ is a term enhancing equitable resilience based on the proportional fairness measure (Abdel-Hadi and Clancy, 2014; Pioro and Medhi, 2004).

The optimization problem (6) is a convex program that can be solved efficiently to find a unique solution. A convex function has only one global minimum, meaning any local minimum is also the global minimum. Thus, in solving this problem, we are guaranteed to find a global minimum, ensuring the quality of the resulting solution.

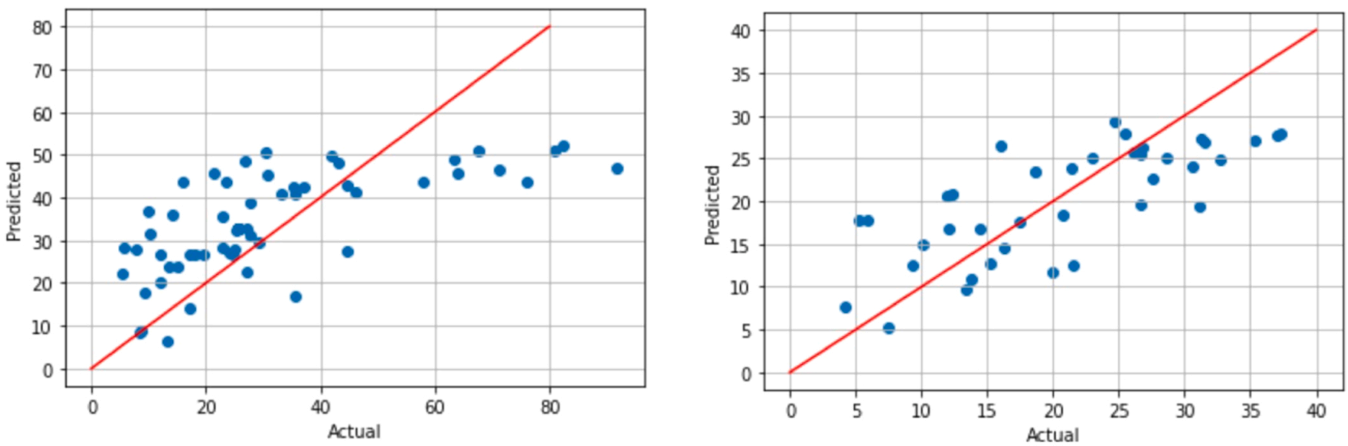
5. Case studies and discussions

In this section, we use case studies to demonstrate the proposed framework for equitable resource allocation to combat power resiliency inequity.

5.1. Learning the predictive model

Intuitively, an explainable predictive model has the following features. The learned coefficients β_1 and β_3 should be negative as they indicate lower levels of inequity experienced by the ZIP i, whereas β_2 is expected to be positive, meaning a higher percentage of residents belonging to minority groups will cause the model to predict higher levels of inequity.

In setting up the regression model, the feature data is first normalized on a scale from 0 to 1 in order to learn similar values for β across variables and better understand the influence of each on equitable resiliency. A 70%– 30% train-test split was used to yield the train and test sets from the set of all ZIP codes, selected at random. The model first returned a Mean Square Error (MSE) of 245 and is not a good fit for the outliers with extremely high levels of power resilience inequity, as illustrated in Fig. 11(a). This is likely due to absent EV charging infrastructure, as previously stated. These outliers are removed and the model is retrained, yielding an MSE of around 40 as shown in Fig. 11(b). The coefficients learned by this version of the model are used in later R_i prediction. Note that although the areas with the highest R_i values are



(a) (b)

Fig. 11. (a): The performance of the regression model for R_i for all ZIPs. (b): Model performance excluding outliers.

those most in need of EV charging infrastructure to mitigate inequity, through additional infrastructure allocation these areas will be brought into the range of R_i for which the predictive model becomes valid.

The coefficients learned are as follows:

$$\beta_0 = 21.3, \quad \beta_1 = -6.3, \quad \beta_2 = 10.3, \quad \beta_3 = -15.3.$$

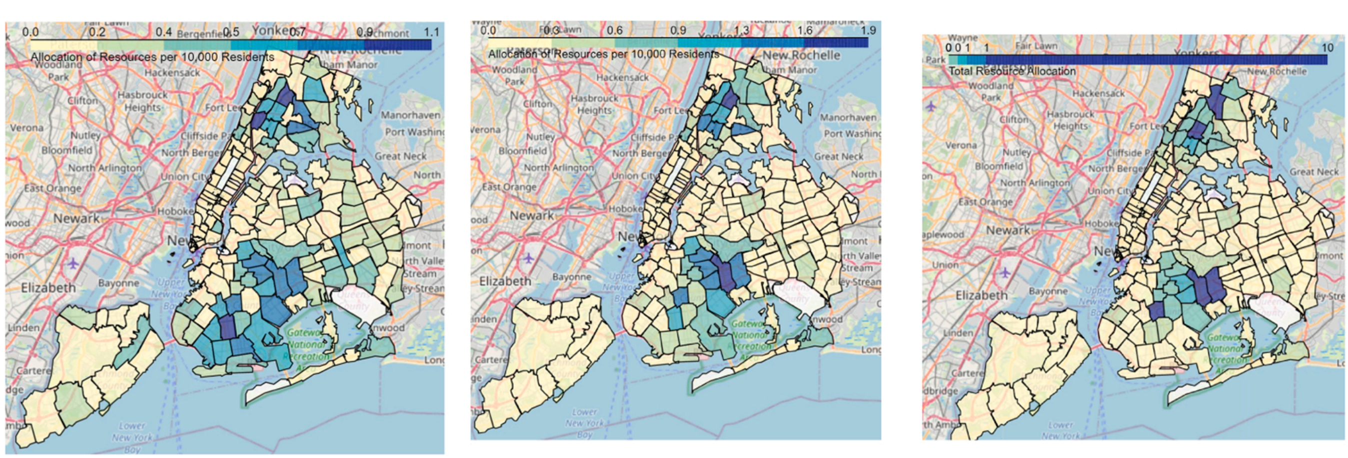
The residual sum of squares (RSS) and R^2 are used to measure the quality of fit. The results are $RSS = 0.47$ and $R^2 = 0.53$, respectively, for the test data. It can be seen that the signs of all coefficients match the expectation. Specifically, β_1 has less influence in this model than the other variables, presumably because many ZIP codes across the city are lacking EV charging infrastructure altogether. In comparison, the income feature I_i has the strongest correlation with R_i.

5.2. Equitable resource allocation

With the learned model, the next step is to decide the allocation of EV charging infrastructure to promote equitable power resiliency in the city. To this end, CVXPY (Diamond and Boyd, 2016) is leveraged to solve the optimization problem (6). For the purposes of this study, we consider $B = 200$ total stations for allocation across the boroughs. Further, we choose $\eta_i = \eta, \quad \forall i \in \mathcal{N}$. By adjusting η, the allocation results can be observed with different importance given to equity and efficiency. We approximate the distribution of demand for EV charging infrastructure ρ_d in (6) according to the population density in the city. The estimation of this parameter can be more accurate if the data on public charging needs becomes available.

Resource Allocation Decision-Making: As desired based on revealed power resilience inequity levels in certain regions, most resources are allocated to the areas with historically high R_i values: Brooklyn and the Bronx. As observed in Fig. 12, when the chosen value for η is low, efficiency is the main concern for resource allocation decision-making. Hence, demand is prioritized based on the population in each ZIP code. When the η value chosen reflects more of a preference for equitable allocation, the resources distributed concentrate more in Central Brooklyn than in South Brooklyn where demand is higher. The resource allocation scheme can be adaptive according to the evolving needs for equity and efficiency.

Improvement on Power Resilience Equity: The resulting improvement of power resilience equity can now be observed after calculating new values for E_i in each ZIP. As shown in Fig. 13, though E_i does not change drastically, all ZIP codes that previously do not have any accessible public EV charging infrastructure have seen improvements in E_i. The resulting R_i values after allocation is depicted in Fig. 14. Power resilience inequity decreases across the city in the areas where R_i was previously highest. Though these areas are still likely to experience the



(a) (b) (c)

Fig. 12. (a): EV charging infrastructure allocation plan across NYC under $\eta = 0$. In this case, the model focuses exclusively on efficiency. (b): Allocation under $\eta = 500$ (considering both equity and efficiency). (c): Allocation plan when the focus is solely on equity (KL divergence term is neglected).

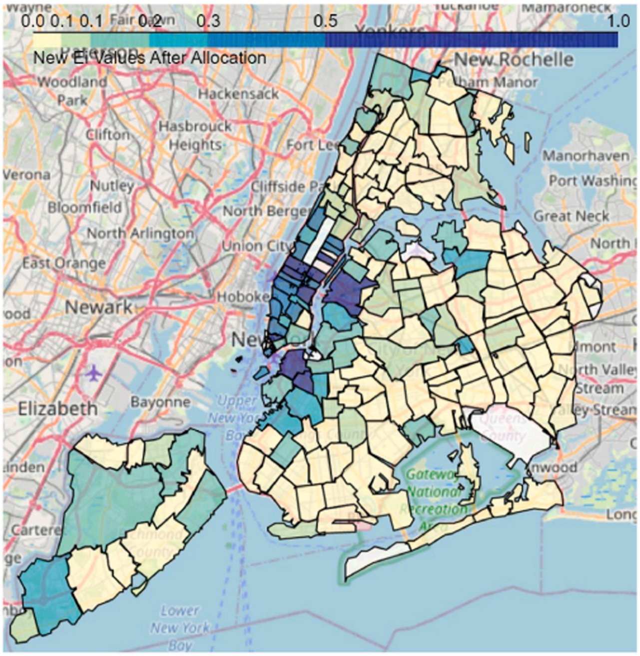


Fig. 13. Heat map of new values for E_i across all ZIPs after the allocation of additional EV charging stations.

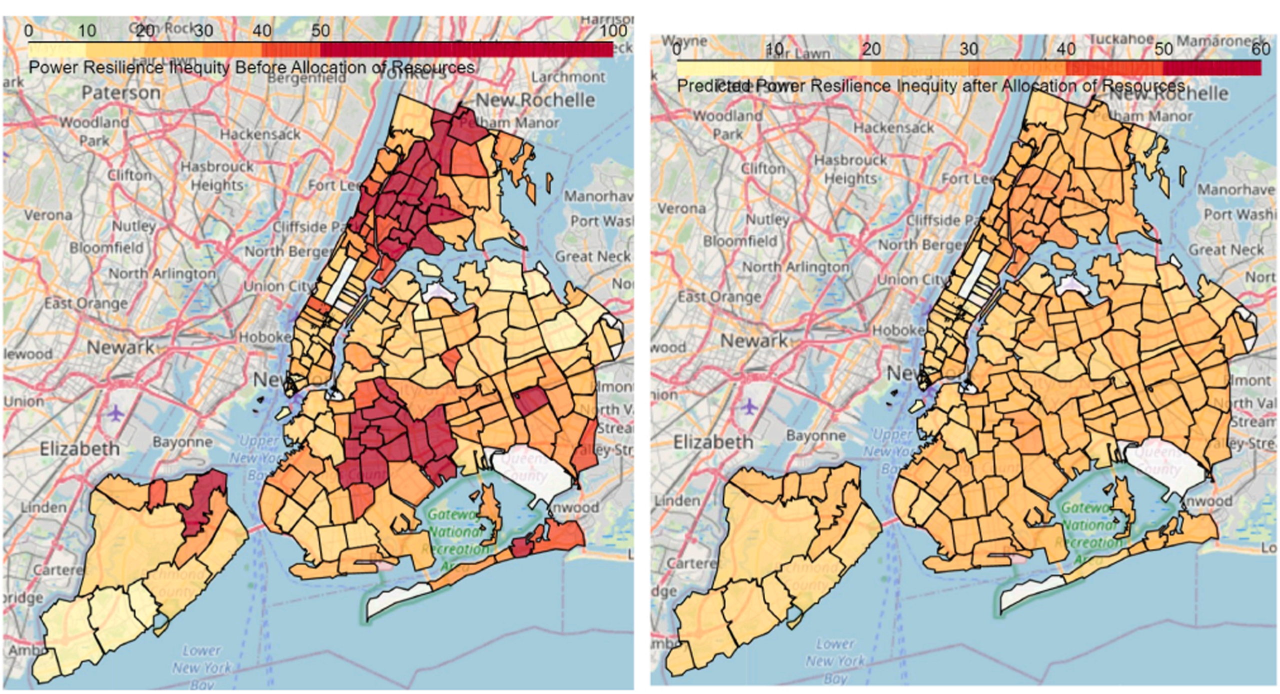
highest degrees of power resilience inequity, the extremity of this inequity is drastically reduced compared to the one before the additional EV charging infrastructure allocation. In other words, power resilience equity is significantly enhanced based on the proposed strategy.

With the equitable allocation framework, this work has strengthened power resilience in the neighborhoods with the greatest need to help prevent and mitigate power failure-related hardship in vulnerable communities specifically, in contrast to the many studies that focus primarily on vulnerabilities in the grid and its power lines rather than the people affected. There is profound value in the framework's flexibility, as it is general enough for parameters to be tuned and changed, i.e., with the introduction of new parameters, while still yielding quantifiable results. The case studies providing these results allow for a more precise assessment of the framework's utility than the qualitative evaluations in Lin et al. (2022). The NYC setting, while specific for the purposes of this study, is also flexible and can be changed by training the model on data from a different setting to yield a decision-making plan fitted to its socio-demographic differences.

6. Conclusion

It is critical that New York State invests in EV charging resources for fair allocation across NYC. Residents can evolve their power consumption as we develop urban areas to be more sustainable, and be empowered to utilize new and developing technologies in improving power resilience in their communities, even as the city looks toward a future of more frequent natural disasters. This work has used data-driven approaches to uncover existing power resilience inequity in NYC and developed an optimization framework to guide the optimal allocation of EV charging infrastructure resources to mitigate such inequity. Our mathematical optimization framework achieved a balance between resource utilization and equity. The proposed scheme has been effective in yielding favorable changes in power resilience inequity, especially for those neighborhoods with the worst power resilience levels. Notably, some of these communities have seen significant decreases in power resilience inequity levels of up to 40% under the developed strategy.

The quantifiable and equitable result of this study highlights the progress made in introducing an equity objective to an optimization framework for strengthening power resilience, making progress against previous related works that either do not consider equity as in Ghasemi et al. (2021), or do not quantify the positive effect of their resilience frameworks with case studies, as in Lin et al. (2022). However, there are limitations to the model in that New York has not yet invested



(a) (b)

Fig. 14. (a): Power resilience equity, R_i, prior to resource allocation. (b): Predicted R_i after resource allocation on a similar scale for easy comparison. The inequity is drastically reduced.

substantially in EVs, resulting infrastructure accessibility coefficient that is not as influential over the model as the demographic coefficients. This not only causes some inaccuracy in the regression model for inequity prediction as previously noted, but may also make the model more difficult to apply to the many cities with less developed public EV charging infrastructure. As more cities begin to prioritize renewable energy and electric vehicles in the next decade, this framework will become more applicable.

A compelling extension of this work would be investigating additional planning and operational strategies to improve the equity of urban power resiliency, such as backup power installation in communities and equitable power dispatch plans.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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