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MULTI-AGENT SIMULATION BASED FRAMEWORK FOR POWER RESTORATION TIME ESTIMATION AT DISTRIBUTION LEVEL

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ABSTRACT

The growing frequency of power outages has prompted increased interest in developing a more resilient power grid that can quickly recover from weather-related damage. At the distribution level, power restoration is a complex, multi-stage process involving multiple response entities. Providing utility stakeholders, government regulators, and the public with information about outage duration and estimated time to restoration is crucial. The research employs a multi-agent simulation approach, which allows for the simulation of decision-making behaviors among different entities and the incorporation of various uncertainties. Specifically, the study uses the open-source simulation package Mesa-Geo in conjunction with the Python language and constructs a road network using the open-source network extension pgRouting for routing queries. The research design includes several experiments focused on Florida as a case study, comparing repair crew sizes, power outage numbers, and road damage scenarios. The findings could offer valuable managerial guidance on resource allocation in the restoration process.

1 INTRODUCTION

The frequency and intensity of power outages are on the rise due to extreme weather events (hurricanes, wildfires, ice storms, flooding, heat waves, etc.) caused by climate change, with the majority of major outages in the U.S. being weather related. Specifically, about 83% of major outages in the U.S. between 2000 and 2021 were attributed to weather-related events (Executive Office of the President 2013). According to one source, the economic cost of these outages is estimated to be between $18 billion and $33 billion annually (Executive Office of the President 2013). According to other sources, the economic cost is between $25 billion and $70 billion annually (Campbell 2012; Taylor et al. 2022). The most recent major weather-related power outages include: Winter Storm Uri (Feb 2021) in Texas, which caused power outage to about 4.5 million households at the peak (Busby et al. 2021); Hurricane Irma in Sep 2017 (one of the strongest and costliest hurricanes on record in the Atlantic basin) left 36% of all customers in Florida without electricity at its peak (Mitsova et al. 2018); Hurricane Michael in Oct 2018 affected nearly 400,000 electricity customers primarily in Florida Panhandle, and it took around 23 days to restore power (Kar et al. 2022). To reduce life losses and economic cost as much as possible, power restoration is time critical and yet complex which greatly depends on available resources, road accessibility, restoration strategies, infrastructural vulnerability, etc. Since roughly 90% of the power outages occur at the distribution systems (Executive Office of the President 2013), this study focuses on the power restoration time estimation at the distribution system.

Current research on power outage duration and restoration time estimation can be classified into three main categories: statistical learning and empirical fitting, optimization-based approaches, and simulation-based approaches. Statistical learning models, such as random forest (Nateghi et al. 2014) and accelerated failure time models (Liu et al. 2007), can predict power outage duration and estimate restoration times. Optimization-based approaches can minimize customer interruption duration (Xu et al. 2007) and minimize cost by determining optimal combinations of internal (Safaei et al. 2012) and external power restoration workforce (Lei et al. 2019). Simulation-based approaches, such as discrete event simulation (Cagnan and Davidson 2007) and agent-based simulation (Walsh et al. 2018), can represent real-life restoration processes, provide quantitative restoration curves with uncertainty bounds, and test possible case scenarios for decision support.

Each approach has its own advantages and disadvantages. Statistical learning models and simulation-based approaches require large amounts of data, while optimization-based approaches are limited by model and computational complexity. Agent-based simulation can replicate past restoration processes and easily test possible case scenarios in the future with more available data.

2 SIMULATION FRAMEWORK FOR POWER RESTORATION

This section describes a framework for simulating the restoration behavior of utilities using multi-agent simulation. The aim of this simulation is to estimate the required restoration time. Agent-based modeling tools such as NetLogo, Repast, and MASON are widely used, but they require customized coding languages and environments. To address this, the Mesa simulation package, which is an open-source Python package (Masad and Kazil 2015; Kazil et al. 2020), is used. Mesa allows users to create agent-based models using built-in core components or customized implementations, visualize them using a browser-based interface, and analyze their results using Python's data analysis tools. Additionally, Mesa-Geo is a geographical information science extension of the Mesa simulation framework that can handle spatial data and work with geographical explicit agents (Wang et al. 2022; Andrew Crooks 2023).

The simulation process involves several agents. The decision-making flowchart among these agents is presented in Figure 1. The damage assessment agent collects information on damage status from social media or field inspections and reports it to the utility company. The utility company then locates the malfunctioning components and allocates repair tasks based on priority ranking preferences, such as affected customer numbers or critical service facilities. The repair crew team navigates to the fault location for repair activities. The city transportation agent is responsible for clearing damaged road segments and reporting the information to the utility company.

During the repair process, the outage repair crew team checks the fault conditions and may require extra equipment from resource agents. Each utility company is responsible for faults in their own service area, but mutual assistantship among utility companies may be considered. Once an outage is repaired, the repair crew team reports to the utility dispatch center and moves on to the next allocated location.

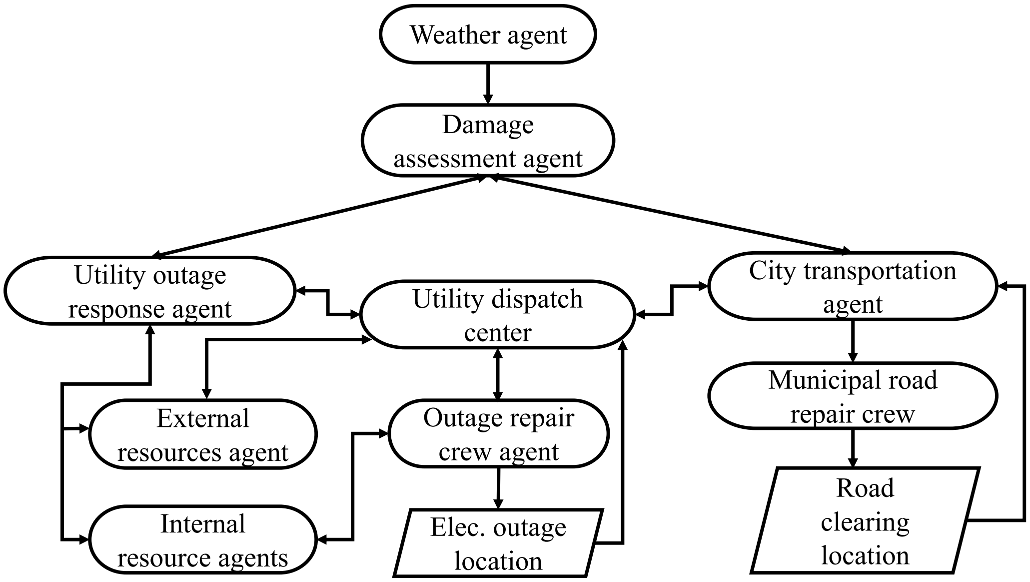

Figure 1: Decision flowchart in multi-agent simulation based framework in power restoration.

3 PRELIMINARY CASE STUDY IN FLORIDA

The state of Florida is selected as the case study location due to its susceptibility to various types of extreme weather. OpenStreetMap is used to obtain road network data for Florida, with only primary and secondary roads selected. The substation location dataset of Florida is obtained from the Homeland Infrastructure Foundation-Level Data (HIFLD) open data source. Routing APIs like Google Map API can be considered for the routing of utility repair crews, but these APIs are generally not open source and may be limited by the number of requests per minute. To overcome this limitation and handle high-frequency routing requests in large-scale simulations, pgRouting is used. pgRouting is an open-source network analysis extension built on PostgreSQL and PostGIS, enabling better customization and the creation of road segments based on road damage conditions. The developed simulation visualization is shown in Figure 2, which displays the moving track of the repair crew and the status of outages. The right-side panel shows the dynamic change in the number of remaining substation outages and households without power.

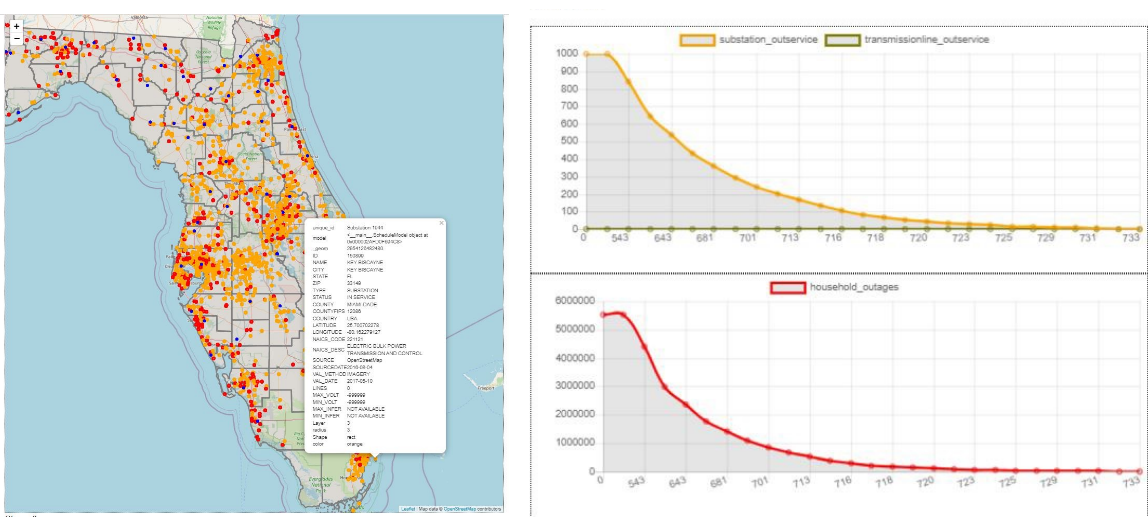

Figure 2: Simulation visualization of Mesa-Geo package in Python.

Due to the data and computational resource limitation, the following assumptions are made in this preliminary studies:

- Only substation outages are considered. Red dots in Figure 2 map are the substations with outages. Orange dots are substations that are functional. The attributes of each substation, such as id, location coordinates, attached households, etc, could be displayed by clicking the dot. Substation outage number is assumed at one of the four levels [100, 500, 1000, 1500]. Repair time of substation is randomized in the range of 1 hour and 2 hours. Household attached to each substation is randomly generated in the range of 1000-10000.
- Each county is assumed as one utility service area with the boundary. Blue dots of each county in Figure 2 map are the staging area which are randomly chosen from the list of large supermarkets or schools with large parking area. Each county is assumed to have same number of repair crew at four levels [5, 15, 25, 35].
- When road damage is considered, the damaged road segments are randomly pick from Florida road network and the damaged number is fixed to be 500 for this work. Repair time of damaged road segment is also randomized in the range of 1 hour and 24 hours.
- Simulation timestep is set to be 1 hour in this work. Note that different timestep settings (e.g., 1 min, 1 hour or 2 hour) require different computational effort and provide different detail levels in simulation visualization, but it won't have impact on final results.
- The shifting schedule, lodging, resting and meal time are not considered for crew agent in the simulation.

A variety of experiments were conducted based on the established settings. The simulation steps without considering road damage are displayed in Figure 3, depicting the curve of customer households experiencing outages. Each sub-figure of Figure 3 has four curve clusters from lower to higher that correspond to different substation outage numbers [100, 500, 1000, 1500], same for the Figure 4. Each curve cluster consists of 5 curves corresponding to the 5 experiments that were run for each substation outage level. The y-axis denotes the initial households number experiencing outages, which depends on the substation outage number level ranging from 100 to 1500. The x-axis represents the steps used to complete the simulation.

In the first sub-figure of Figure 3, when the number of repair crew teams for each county is 5 and the total substation outage number is 1500, the restoration is projected to be completed in 57 hours. Increasing the repair crew team number to 15 reduced the estimated restoration time to less than 19 hours with a maximum substation outage number of 1500. The restoration time with 1500 outages decreased to about 13 hours when the crew team was increased to 25, and remained constant at this level even as the crew team number for each county was further increased to 35.

In the event of road damage, as indicated in the contract with the simulation settings for 500 damaged road segments, the curves showing the number of households with outages are presented in Figure 4 for various crew team numbers. The results show a significant increase in simulation steps for crew teams of 15, 25, and 35 when road damage is considered, in contrast to the findings in Figure 3. However, for a crew team of 5, the simulation steps did not increase but rather decreased slightly, especially for a substation outage level of 1500. Figure 5 illustrates the detailed range of steps, with each box indicating five runs. The simulation steps and their variance increased for outage levels 100 and 500, but decreased for levels 1000 and 1500. This outcome is mainly because the repair time for road damage is randomized within a range of 1 to 24 hours, and crew teams of 5 are relatively insufficient for outage levels of 1000 and 1500, with the majority of road damages being repaired before the crew team has completed the restoration of the remaining substation outages. Thus, road damage has less impact on the simulation steps for outage levels 1000 and 1500 in the case of a crew team of 5. The simulation steps' variance increases when the outage level is relatively low at 100 and 500 since road damage constrains the routing when the outage number is low, and the crew must choose an alternative route or wait for damages to be repaired before reaching specific substations.

For crew teams of 35, as shown in Figure 6, the simulation steps' variance increases significantly when road damage is considered. This is due to the crew team's restoration time being less than 24 hours for all outage levels, making road damage a major constraint in this situation. A similar situation can be observed in Figure 5, where the step variance increases for outage levels of 100 and 500 because the restoration time for these two outage levels is generally less than 24 hours. But with outage levels of 1000 and 1500, the overall restoration time with 5 repair crew team will be great than 24 hours, thus road damage doesn't play a significant role here. The constraints from road damages result in a longer near-flat tail in the sub-figures for crew teams of 15, 25, and 35 in Figure 4.

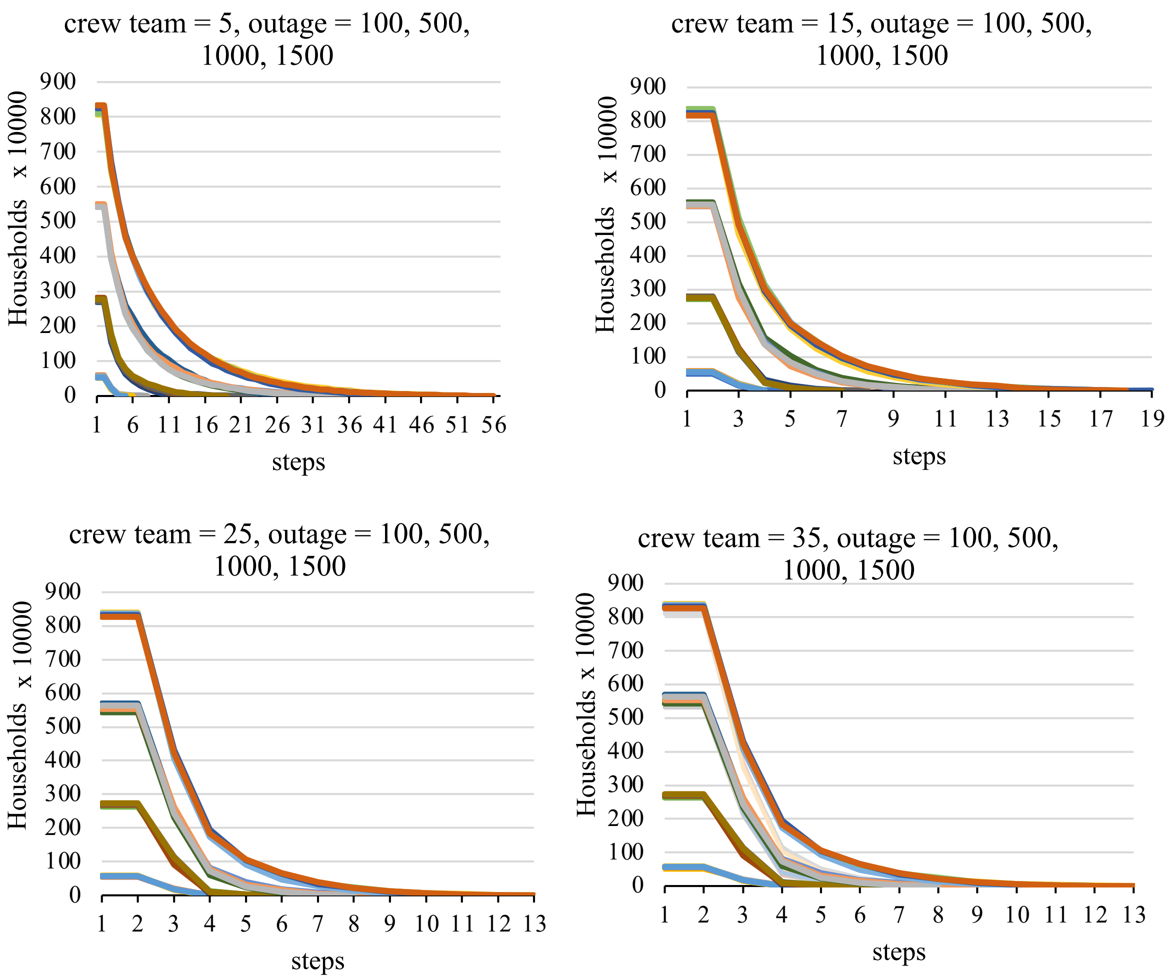

Figure 3: Household number with outages following the steps (without considering road damages).

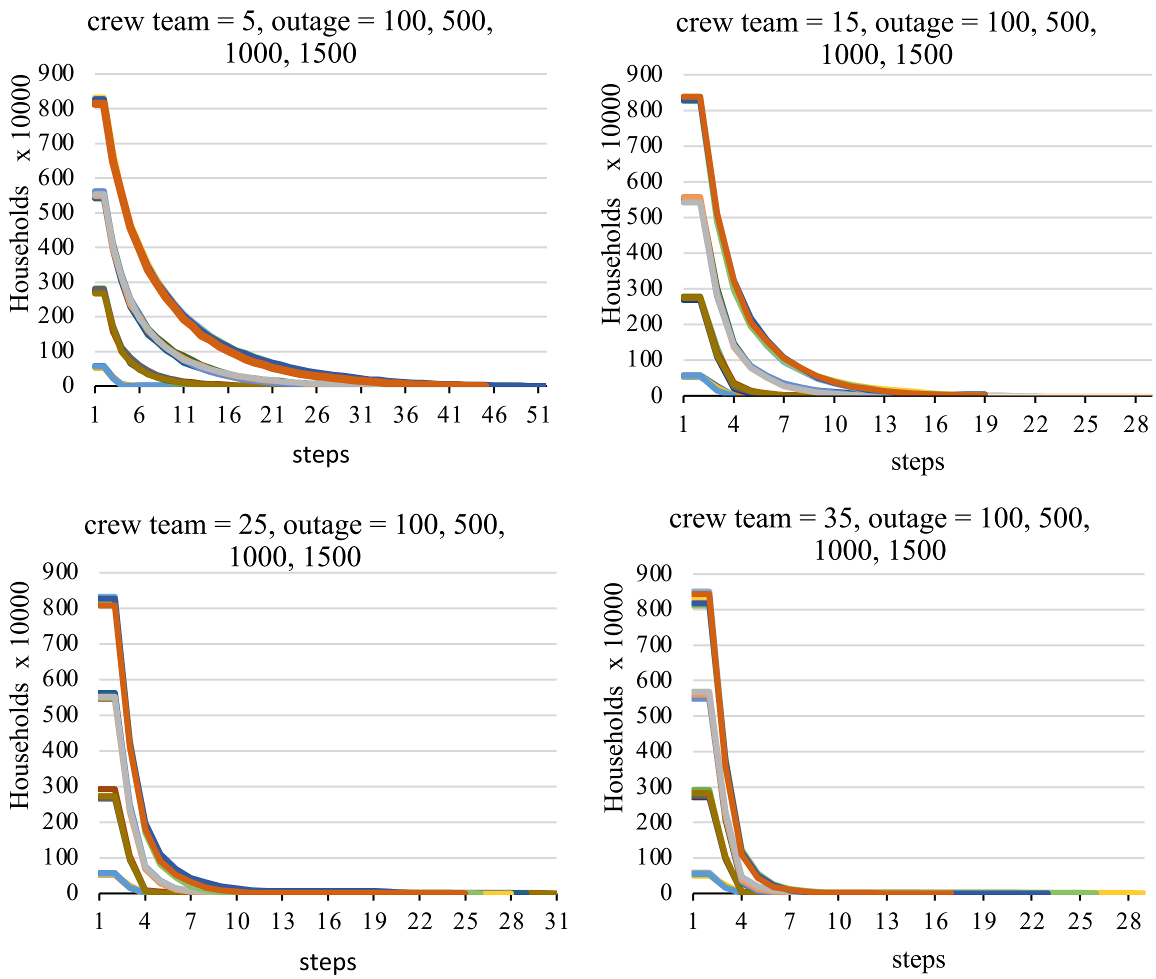

Figure 4: Household number with outages following the steps (considering road damages).

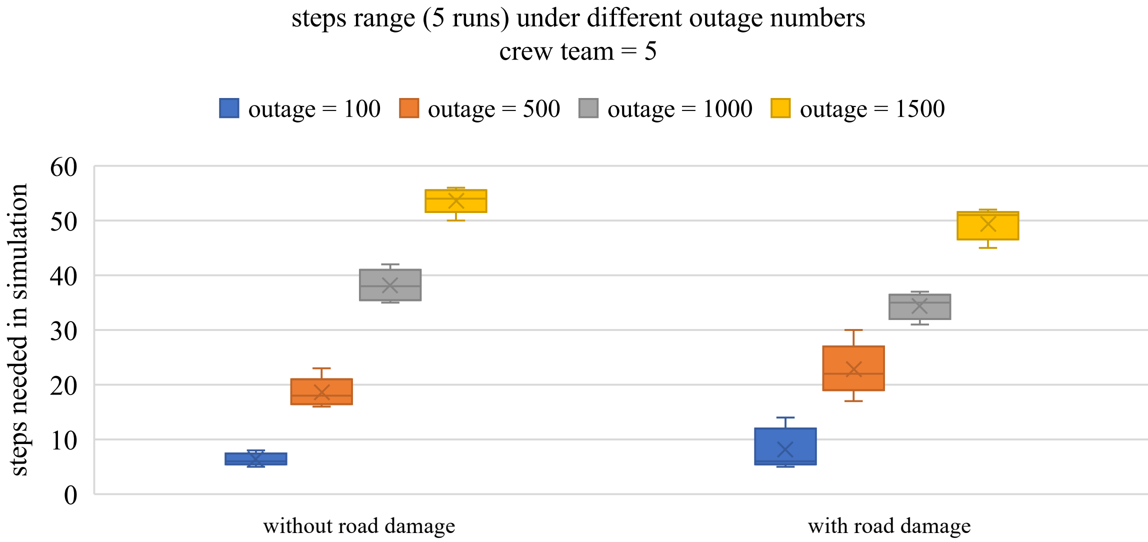

Figure 5: Simulation steps range plot with/without road damage (crew team = 5).

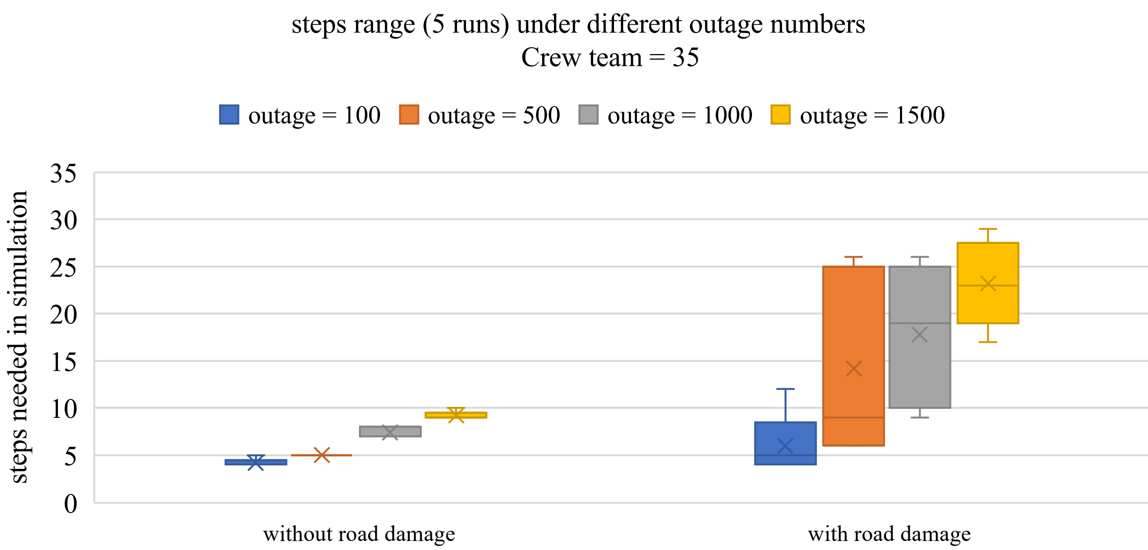

Figure 6: Simulation steps range plot with/without road damage (crew team = 35).

As previously noted, each utility company is considered as a distinct entity. The average time taken for each utility company/county to complete restoration can be computed, as illustrated in the two scenarios depicted in Figure 7. Counties such as Hillsborough, Miami-Dade, and Polk generally require a longer time to restore services due to the higher concentration of substations in the region or because the road network becomes inaccessible once a road segment is damaged. Based on the results at the county level, a restoration time map can be generated, as shown in Figure 8.

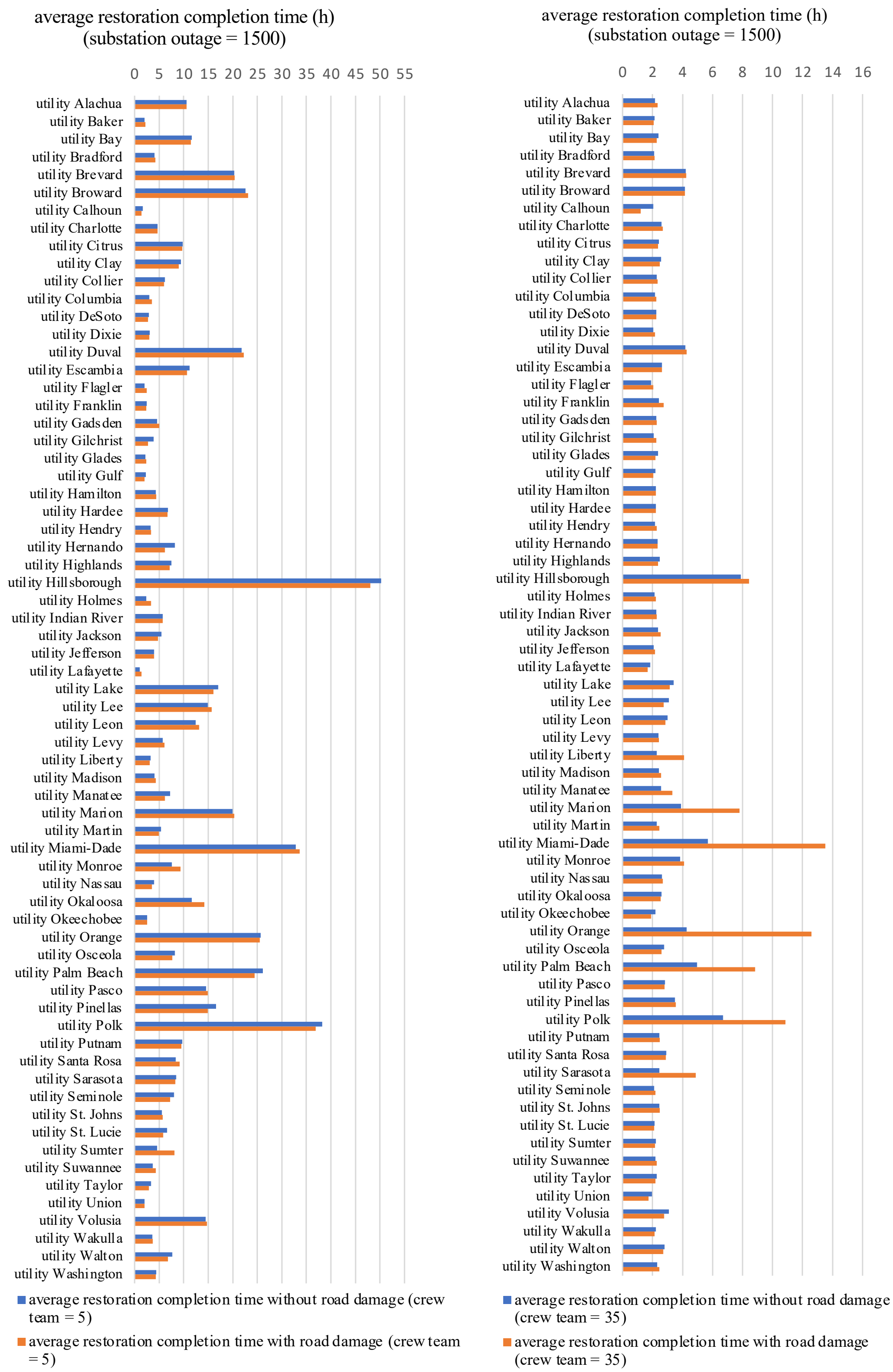

Figure 7: Average restoration completion time of each utility company/county.

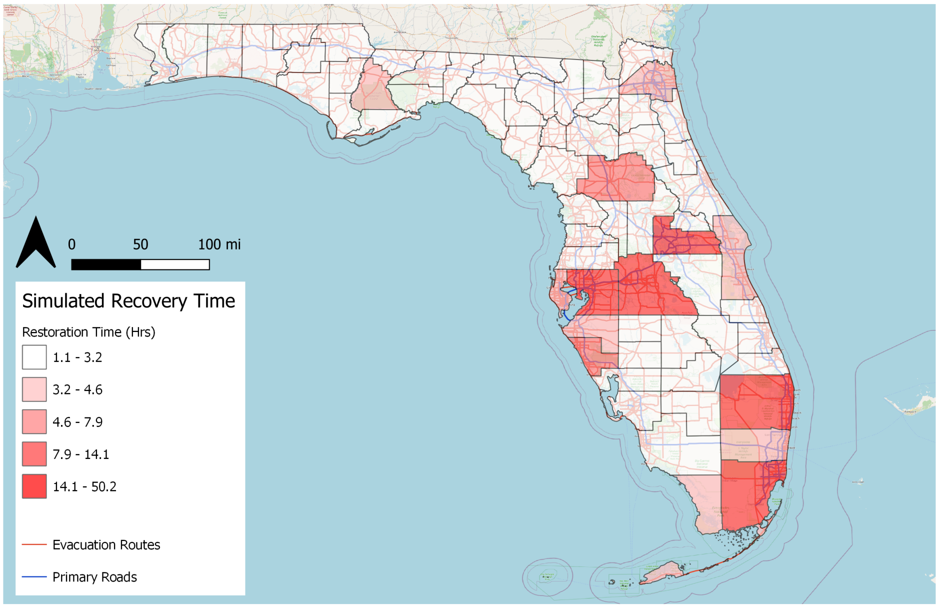

Figure 8: Simulated recovery time map: substation outage number = 1500, crews per county = 35, road damage = 500 segments.

4 CONCLUSION

This study presents a preliminary framework using a multi-agent simulation approach to estimate the time needed to restore weather-induced power outages. The simulation is based on the open-source agent simulation package Mesa-Geo in Python. The substation and road network data of Florida are used as case studies, with a focus on important variables such as repair crew number, substation outage number, and road damage. Although the simulation makes certain assumptions and is relatively simple, it provides valuable insights into restoration trends that can be used by utility companies to deploy resources and workforces more effectively, inform customers about the estimated restoration time, and so on. The simulation can be further developed to become more practical in several ways, such as by defining more precise utility service areas, improving road damage assessment based on the hurricane path, and taking into account the shift schedules of repair crews.

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