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RePOWRD: Restoration of Power Outage from Wide-area Severe Weather Disruptions

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OAK RIDGE National Laboratory

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DOE-CESER Program
Work Performed under EAGLE-I Agreement

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ACRONYMS

ABM	agent-based model
API	application programming interface
BES	bulk electric system
DOE	US Department of Energy
EAGLE-I	Environment for Analysis of Geo-Located Energy Information
EIA	Energy Information Administration
ETR	estimate time of restoration
MLR	multiple linear regression
NHC	National Hurricane Center

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ABSTRACT

The purpose of the RePOWERD project is to develop a probabilistic and a simulation based power restoration forecasting model for tropical storms based on geographic utility service areas, impacts to energy infrastructures and transportation networks, time-varying customer outage number, crew information (i.e., crew size, crew staging requirements), and utility restoration plans. Energy infrastructure is a critical lifeline essential for the United States' national and economic security. Like other critical infrastructures, this infrastructure is aging and is at a high risk of damages from extreme weather events. Based on the number of reported outages in EAGLE-I during 2020 and 2021, it is evident that the current energy infrastructure is not equipped to handle extreme event impacts and will contribute to significant outages. From a resilience perspective, it is essential to forecast restoration time in the event of a severe weather induced power outage to assist the US Department of Energy, emergency managers, and first responders with resource planning. This project contributes to this crucial need. This report details the models, that were developed in this pilot study, to determine the rate of restoration and estimated time of restoration (ETR) during tropical storm events within counties and utility service areas based on damage to energy infrastructures and total number of customers experiencing outages.

1. INTRODUCTION

Electric power is a critical lifeline that is essential for the functioning of critical assets and daily lives [1], [2]. The US energy infrastructure is aging and is at high risk of being adversely impacted by extreme weather events, thereby contributing to longer power outages. A study by McKinsey Global Institute (2020) [3] reported that while wind power might be resilient to drought, thermoelectric and hydropower plants are at risk of losing functionality due to water shortages. Likewise, higher temperatures and heat waves may reduce the efficiency of the grid and adversely impact the physical condition of transmission/distribution system components [3], making the grid unable to meet increasing demand due to climate change.

Reduced efficiency and damage to energy infrastructures are already recognized as major causes of wide area power outages. In 2017, Hurricane Maria damaged energy infrastructures in Puerto Rico and caused citizens to go without power for months [4], [5]. Even now, more than 4 years after the hurricane, the energy grid of Puerto Rico is still not reliable. In August and September 2021, the island was forced to undergo rolling blackouts that left millions of customers without electricity due to surging demand the grid could not meet [6]. Likewise, energy infrastructure of the US mainland also appears to be fragile and ill equipped to handle changing demands and extreme event impacts. Hurricane Ida that made landfall on August 26th, 2021, in Louisiana, left 1.2 million customers without power in eight states including Louisiana, where the event damaged 30,000 utility poles and left parts of the state in the dark until September [7], [8]. Winter Storm Uri (February 2021) left more than 4.5 million customers without electricity in Texas [9], [10]. In California, rolling blackouts begun due to a public safety concern during wildfires and later continued to address the increasing electricity demand during heat waves that left millions of California customers without power in 2020 and 2021 [11], [12]. According to the Energy Information Administration (EIA), the US customers experienced over eight hours of power outage in 2020 (the most since 2013) due to extreme weather events [13]. These widespread outages are not only concerning from a public health perspective, particularly during the COVID-19 pandemic, but also contribute to significant financial losses.

Annually, power outages in the US cost ~$70 billion [14]. Winter Storm Uri reportedly caused nearly $130 billion in loss and more than 100 deaths in Texas [15], [16]. Extreme weather events are becoming common and costly and are expected to cause longer and more frequent power outages with devastating impacts [17], [18]. While overhauling the energy infrastructure and expansion of renewables are priorities to reduce power outage duration and impacts, restoration of electricity supply services after major extreme events (e.g., hurricanes) is critical to system interdependency within the energy sector and across the nation's critical infrastructure sectors. Given the proprietary nature of energy infrastructure, utility companies in the US have their own models to forecast power restoration times. Beyond being disparate, their modeled outputs are not readily available to the US Department of Energy (DOE) to analyze system vulnerabilities and support infrastructure protection programs. Current National Outage Model data do not provide information about restoration time, and inferring restoration time from outage data has several uncertainties because (1) the cause of the outage is not available and trying to fit events to data is not feasible; (2) while the decrease in outage numbers may generally be regarded as a restoration, it is not always the case (e.g., it could be due to error in the initial reporting or people may have evacuated after an event); and (3) daily outage data could be from different events and the delineation of those events is not feasible. By developing power restoration forecasting models, the RePOWERD project contributes to this crucial need.

The purpose of this project is to develop a probabilistic and a process-oriented simulation model to estimate restoration time in distribution systems in case of extreme weather events that can be used to assist DOE as well as emergency managers and first responders with resource planning. In this pilot study, we developed and deployed three models – an exponential decay function, a multiple linear regression (MLR) model, and an agent-based model (ABM). These models were developed using power outage data available from DOE's EAGLE-I[1] (Environment for Analysis of Geo-Located Energy Information) platform for Category II[2] and above hurricanes that have impacted the Atlantic and Gulf Coast since 2014. While the exponential decay function was used to estimate restoration time (*ETR)* and rate of restoration (β), the MLR model was used to identify the factors (extent of damage, underlying land use/cover, population density, county type – urban vs rural) influencing restoration time. Because restoration operation requires the involvement of several agencies and agents, the ABM was developed to generate a range of restoration times based on change in agent behavior and interaction with environments, specifically, the variation in utility repair teams, crew size, and crew staging. The following five hurricanes - Irma, Harvey, Michael, Zeta and Laura that impacted the Southeast during 2014 – 2020 were used to estimate *ETR* and β values using the exponential decay function for counties and utility service areas. For these events, the MLR was deployed to estimate *ETR* within counties. The ABM was deployed using hypothetical outage data, crew size, crew staging areas and number of substations affected to compute *ETR*.

This report presents the conceptual framework for the restoration model and discusses the implementation of the models discussed above. Section 2 provides a brief overview of restoration process used by utilities as well as the current state of the art in restoration modeling. The conceptual frameworks, datasets, data processing techniques, and models are discussed in Section 3. The results are discussed in Section 4. Finally, Section 5 presents future work and concluding remarks.

2. RESTORATION PROCESS

Power restoration is a complicated process that involves several steps: (1) determining status of the bulk electric system (BES) system (generation, transmission, distribution) prior to an outage, (2) preparing power plants to address restoration depending upon the cause of outage and extent of damage to system components, (3) restoring generation and critical loads along the distribution network, (4) ensuring the transmission path is energized for power transmission, (5) providing for system synchronization depending upon the system components (transmission, distribution, generation, distribution/transmission system islands), and (6) coordinating between utilities (large vs co-ops depending upon the extent of outage and damages) and city officials to address crew dispatch, crew staging and implementation of safety protocols

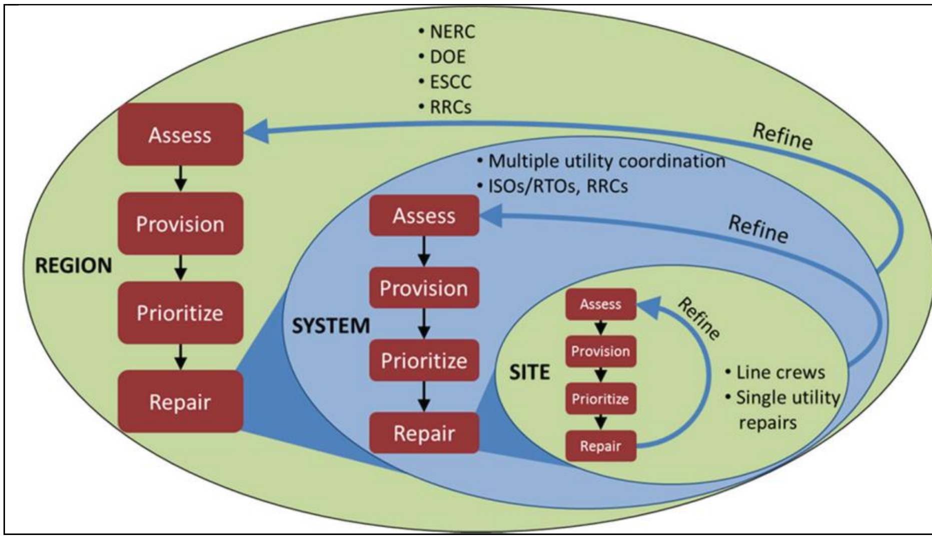
[1] The EAGLE-I platform (https://eagle-i.doe.gov/) is primarily used by DOE – Office of Cybersecurity, Energy Security and Emergency Response.

[2] According to the National Hurricane Center (https://www.nhc.noaa.gov/aboutsshws.php), a Category II hurricane is considered a major storm with a wind speed of 96 – 110 mph. Such an event contributes to damage to energy infrastructures.

to undertake repair of system components [19], [20], [21]. Because the restoration process is designed to minimize restoration time and service interruptions, reduce number of customers without power, and maximize generation capacity, restoration strategies can vary across utilities based on a company's service area and customer base as well as the event that caused the power outage [19], [22]. Hence, restoration planning must begin ahead of time and be designed to adapt to the event to meet the objectives.

Being a critical infrastructure, power restoration planning and modeling has drawn attention from research and industry alike and is not a new concept. Although outages occur both on the transmission and distribution side of the Bulk Electric System, roughly 90% of the outages occur on the distribution side [23]. Several models have been developed to restore power on the distribution side. These models can be categorized into three categories – statistical, simulation and optimization models. Statistical models tend to describe the relationships between outage duration and covariates to predict restoration time across space [24]. These models are increasingly used for restoration planning in case of weather induced disasters [22], [25-27]. Simulation modeling is often used to simulate the operations and interactions to help with determination of restoration steps and estimate restoration time from a decision-making perspective. Walsh et al. [28] and Cagnan et al. [29] implemented an agent-based model and a discrete-event simulation model to describe the restoration process following storm and earthquake events, respectively. These models allow estimation of a range of restoration durations under different event conditions and impacts. Although similar to simulation models in terms of iteratively estimating restoration time, optimization models determine the best process to minimize restoration time and maximize load capacity. Several optimization models have been developed to identify the energizing path, dispatch of repair crews and the use of distributed generators to reduce restoration time, and dispatching decisions [30-32].

Effective restoration requires utilities and other agencies such as the Department of Transportation and local governments (city and/county planning and emergency management agencies) to coordinate and collaborate to ensure restoration time can be minimized. While utilities are responsible for power restoration, DOE is the energy-sector lead agency responsible for coordinating federal actions to expedite the restoration process and to aid with resource planning as needed (Figure 1). However, DOE does not have access to restoration plans. The outage data available on DOE's EAGLE-I platform do not provide information about restoration time and inferring restoration time from outage data is not possible due to lack of information about the cause of an outage. While information about the customers experiencing an outage, the locations where evacuation is underway, and the distribution of gas stations that would be patronized by residents during evacuation and allow using gasoline as an alternate source of energy for generators could be determined through modeling [34-36], these models do not provide a comprehensive overview of the restoration process and agent interaction. To assist DOE with decision-making, in this study, two probabilistic models (using an exponential decay function and a multiple linear regression) and an agent-based simulation model were developed using real-event outage data and hypothetical outage data.



NERC: North American Electric Reliability Corporation
ESCC: Electricity Subsector Coordinating Council
RRC: Regional Resource Centers
ISO: Independent System Operator
RTO: Regional Transmission Organization

Figure 1: Restoration process that occurs at multiple levels by different institutions [33]

3. METHODOLOGY

This section introduces the study site and events that were selected to develop and deploy the first version of the probabilistic and simulation models to forecast restoration time. The section also presents the conceptual framework for restoration modeling and the datasets that were acquired and processed for model development. Finally, the section discusses the three models (exponential decay function, multiple linear regression and agent-based simulation) that were developed using real and hypothetical outage data.

3.1 STUDY SITE AND CONCEPTUAL FRAMEWORK

Tropical storm events are a major cause of power outages. Based on historical events, the Gulf Coast and the Southeast Region in the United States are at a higher risk of experiencing Category III and higher hurricanes at a higher frequency [37]. Given that the coast is home to large urban areas with significant populations and older energy infrastructures, it is not surprising that tropical storms tend to cause significant outages. This study, therefore, focused on developing restoration models using tropical storm events that have impacted the states in the Southeast region during 2014 – 2020 (Figure 2).

The high risk to energy infrastructure from tropical storm events underscores the need to develop a restoration model that is process-oriented to provide situational awareness information about estimated restoration time across an impact area at the county and utility service area levels. Such information would assist first responders and emergency managers with resource planning, allowing them to prioritize where restoration activities could and should occur depending upon critical asset availability and population density. Keeping these needs in mind, the following framework (Figure 3) was implemented in this study that could be adapted to other events to estimate restoration time.

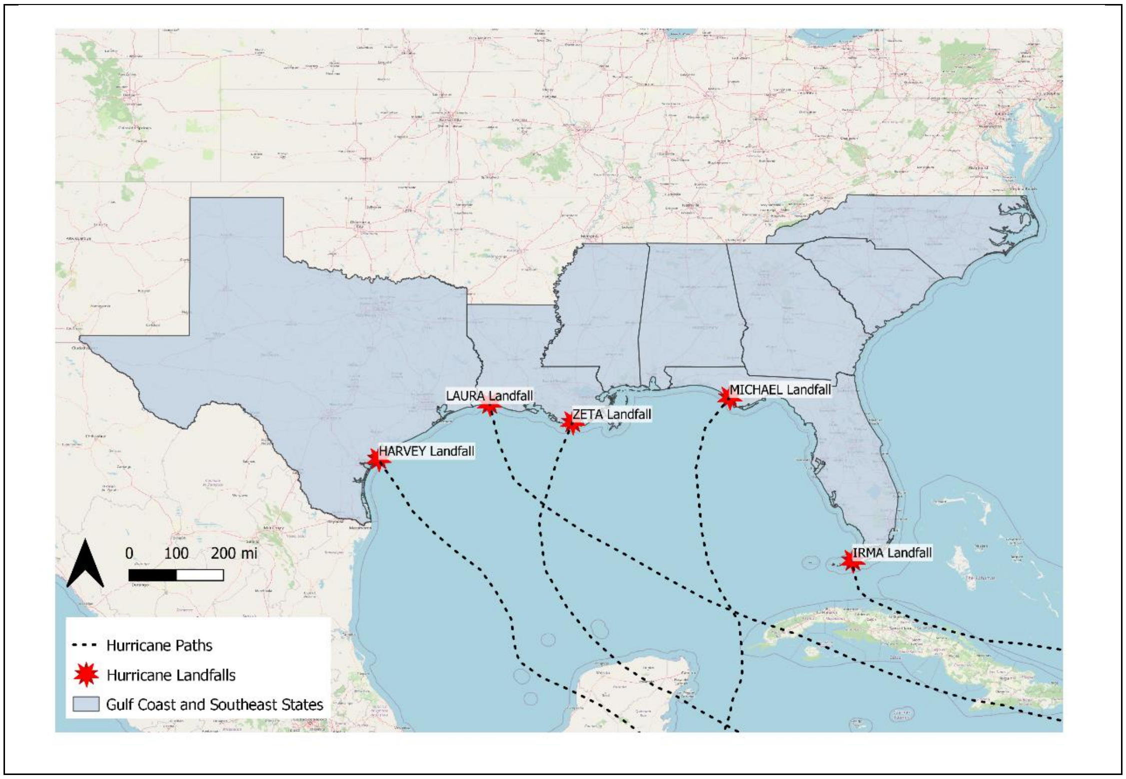


Figure 2: Landfall locations and states impacted by selected hurricanes during 2014-2020

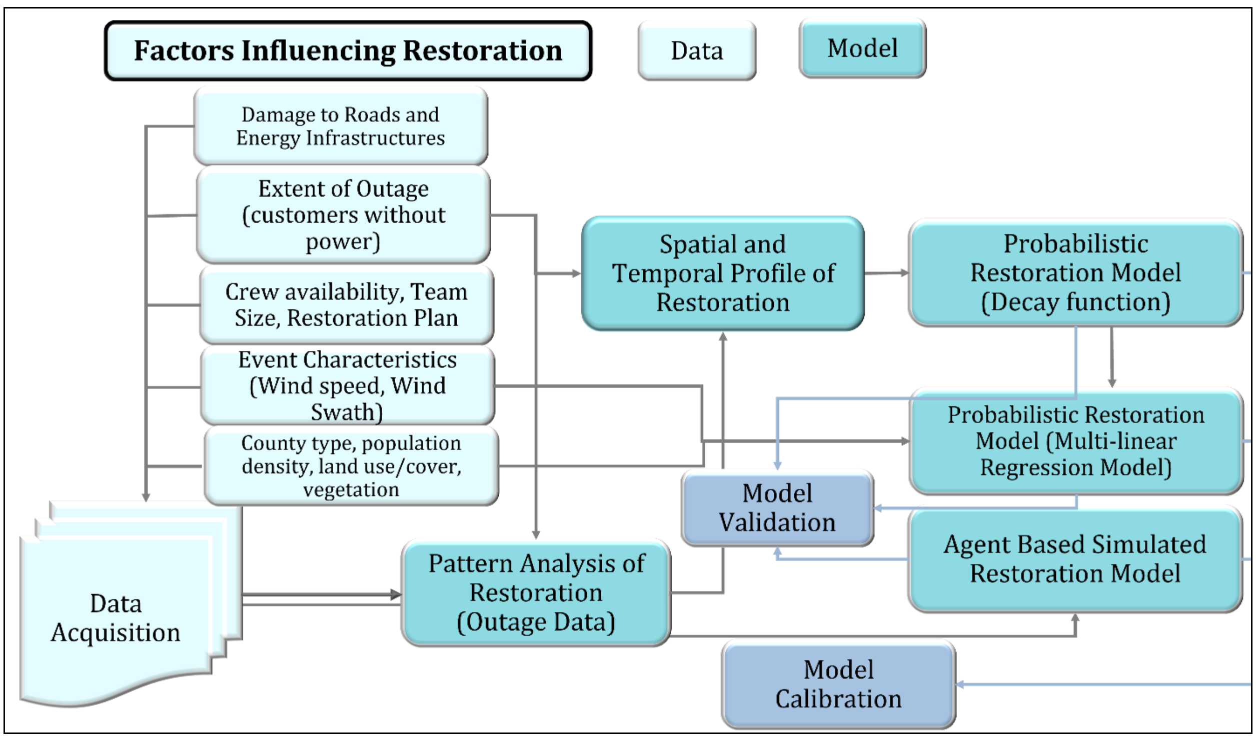


Figure 3: Conceptual framework and components of restoration model

3.2 EVENT SELECTION

Hurricanes vary greatly in terms of their eye size, wind speed, rainfall, pressure, and size of the impacted area. While some hurricanes can cause significant wide-area outages, others hover over one location and contribute to significant flooding and longer-term outages. Considering this variability, we used the outage data for five hurricanes (Irma, Michel, Harvey, Laura and Zeta) that have impacted the Southeast Region since 2017, caused power outages in the order of hundreds of thousands to millions, and required significant mobilization of repair crews. Hurricane Irma (a Category IV hurricane), which impacted southern Florida in August 2017, was approximately the size of Texas [38]. The slow-moving storm engulfed the southern peninsula of the state and impacted some areas for over 24 hours [38]. This caused nearly 60% of Florida's ~10 million electric customers to experience power outages [39]. By contrast, Hurricane Michael (a Category V hurricane) impacted the Florida Panhandle in October 2018 with record sustained winds measured at 151 mph, causing devastating damage over a narrow band measuring ~100 miles east to west [40]. The storm caused about 400,000 power outages, primarily in the Florida Panhandle, and took around 23 days to restore [41]. Hurricane Harvey impacted a narrow band, in Texas in August 2017, making landfall as a Category IV storm [42]. Harvey caused significant precipitation and flooding and led to more than 300,000 outages due to damage to power plants and transmission and distribution infrastructures in Texas and Louisiana [43]. In August 2020, Hurricane Laura was one of the strongest hurricanes to make landfall as a Category IV hurricane in Louisiana in 164 years [44]. In addition to cutting off crude oil production along the Gulf Coast for 15 days [45], Laura also caused significant damage to transmission and distribution systems and left more than 900,000 customers without power in Louisiana and Texas [46]. Hurricane Zeta made landfall in southern Louisiana as a Category II storm in October 2020 [47]. Despite being a Category II hurricane, Zeta caused significant power outage and left more than 2.5 million customers without power in the Southeast Region [48].

3.3 DATA ACQUISITION

Both static and dynamic datasets were acquired for restoration modeling for the five hurricanes discussed above, which are listed in Table 1 along with their sources and dates of acquisition. Outage data for the above-mentioned tropical storm events were obtained from EAGLE-I as well as from the Florida Public Service Commission (FPSC) for Hurricanes Irma and Michael at county and utility service area boundaries. The reported base customer dataset was obtained from the Energy Information Administration (EIA) as well as from EAGLE-I. A road network dataset was obtained from OpenStreetMap, and electric infrastructure datasets (i.e., substation location, utility retail service area boundary, staging areas for restoration) were obtained from the Homeland Infrastructure Foundation Level Data Open Data platform. Event characteristics datasets (i.e., wind speed probabilities, wind swath, hurricane track) for the hurricanes were obtained from the National Hurricane Center (NHC). Given the dynamic nature of the tropical storm data, the RSS feed associated with these datasets was used to obtain data every 6 hours from the NHC site. The county boundary, population count and density data, and county type (urban vs. rural) were acquired from the US Census Bureau. Because trees and vegetation often contribute to distribution level outages, land use/cover data, vegetation/tree canopy data, and impervious surface datasets were acquired using the iTree Landscape tool from the 2011 National Land Cover Database. Because the datasets are available at varying spatial scales, to minimize error variance due to scale impact [49] and avoid data loss, the datasets were aggregated to county and utility service boundaries.

Table 1. Datasets and corresponding data sources used for restoration modeling.

Name	Source	Source URL	Acquisition date
EAGLE-I Outage Tracker Data	DOE EAGLE-I application	N/A, not a public resource	Last updated March 2021
EIA Customer Data	EIA	https://www.eia.gov/electricity/data/eia861/	March 2021
Florida Public Service Commission Customer Data	FLPSC	http://www.psc.state.fl.us/Home/HurricaneReport	March 2021
Florida OpenStreetMap Road Network Data	Geofabrik/OSM	https://download.geofabrik.de/north-america/us/florida.html	December 2020
Electric Substations	HIFLD (ORNL)	https://hifld-geoplatform.opendata.arcgis.com/datasets/geoplatform::electric-substations/about	June 2020
Electric Retail Service Territories	HIFLD (ORNL)	https://hifld-geoplatform.opendata.arcgis.com/datasets/geoplatform::electric-retail-service-territories/about	June 2020
Staging Areas[1]	HIFLD (ORNL)	https://hifld-geoplatform.opendata.arcgis.com/datasets/geoplatform::public-schools/about	August 2021
Wind swath, Wind speed probabilities	National Hurricane Center	https://www.nhc.noaa.gov/gis/	June 2021
Historical hurricane track, Wind speed, Wind swath extent[2]	National Hurricane Center HURDAT V2	https://www.nhc.noaa.gov/data/hurdat/	November 2021
County Boundary	US Census Bureau	https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html	November 2020
Urban vs. rural counties	US Census Bureau	https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural.html	March 2021
Land use/cover, Impervious surface, Vegetation/ canopy cover	Multi Resolution Land Characteristics Consortium	https://www.mrlc.gov/national-land-cover-database-nlcd-2016	March 2021

3.4 DATA PROCESSING

Outage data: The outage data from EAGLE-I record the total number of customers experiencing outages (a.k.a. NCO here onwards) within counties and utility service areas every 15 minutes. The outage data are directly obtained from the utility companies dealing with outages and restoration. Despite high granularity, the reported NCO was not consistent over time, which led to the presence of null values and, in certain instances, higher NCO outside the time of landfall (Figure 4) and several anomalous peak NCOs. A nearest neighbor sampling approach was also used to eliminate null values. These continuous data sets were then used to aggregate the total number of customers experiencing outages within each county and utility service area at different time spans.

[1] This dataset does not contain information on staging areas used by utilities during storm events. Public schools were chosen as a stand-in dataset to improve the ABM in this pilot study.
[2] These data were used to isolate outage records and creating reports on outage durations based on storm path.

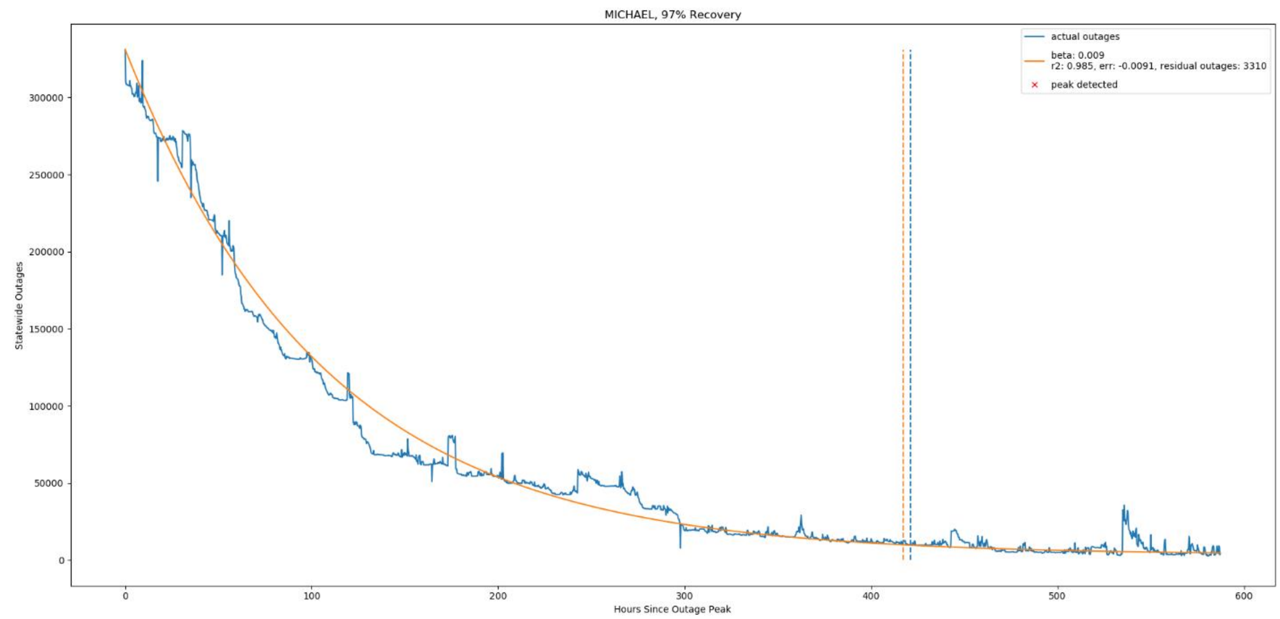


Figure 4: Smoothed outage data for Hurricane Michael (Blue line – original NCO data from EAGLE-I, Orange line – exponential decay modeled NCO, Y axis – total number of customers without power, X axis – hours since peak NCO was reported for the event, Blue and Orange dotted line represent the hours since peak outage when power to 97% of customers was restored for the original and modeled data respectively)

Wind impact data: High wind speed is one of the contributors to large-scale outages resulting from damage to distribution infrastructures. Hence, the wind speed and wind swath data from the NHC were used to examine the extent of impact of wind speed on rate of restoration. The wind swath data record the position of the hurricane at 6h intervals and at three wind speed thresholds (greater than 34 knots, greater than 50 knots, and greater than 64 knots). Using the wind speed thresholds and the wind swath, within each county, the land area (in square miles) and percent land area impacted by a specific wind speed was computed. This land area summarized the exposure to each wind speed threshold within each county. A similar approach was used to compute land area impacted by a specific wind speed threshold within utility service area boundaries. To measure the wind speed contributing to outages, the peak outage counts computed at a 1h window within each county were compared with the forecasted wind speed at the time of outage. The forecasted wind speed aligning with the corresponding outage at a specific time was recorded within the county and/or utility service area. The wind speed data and associated event characteristics were also used to isolate outage records and outage durations that coincided with the path of a hurricane.

Routing and staging data: A major component of restoration is to access the impacted substations for repair and restoration. To identify routes, road network data from OpenStreetMap were obtained. From the entire set of road network datasets, the primary and secondary roads were selected using the following filters: motorways, motorway links, primary roads, primary links, secondary roads, secondary links, trunks, trunk links, tertiary roads, and tertiary links. To create a topological dataset of the road networks for routing purpose, pgRouting, an open-source network analysis extension that builds on PostgreSQL and PostGIS, was used, which ensured that each road network has a node (represented by origin and destination locations) and an edge (represented by the road link(s) connecting the nodes). The nearest-neighbor spatial query was used to identify the nearest road network to each substation. Traveling to a substation is also dependent on the extent to which a road is damaged. To model the travel time due to damage to roads, hypothetical damage information (e.g., 25%, 50%, or 75% of a road is damaged) was assigned to each road network link. Inherently, utilities identify potential staging areas from where crews are dispatched to repair damaged substations and/or distribution lines and poles. Due to lack of information about staging, it was assumed that facilities with large parking lots (e.g., public schools, grocery stores, shopping areas) could be used for staging purposes. As a preliminary dataset, public schools were selected as potential staging areas.

3.5 METHODS

To create a model capable of robust power restoration predictions, it is necessary to study the complex relationships existing among extreme weather events, power infrastructures, human repair crews, and unique geographic areas. Here, we developed and deployed an exponential decay function based restoration forecasting model, a MLR model, and an ABM. While the probabilistic models were implemented using the above-mentioned five hurricanes and the raw outage data from EAGLE-I and FPSC, the prototype ABM was deployed using hypothetical outage data as a precursor to replicate the EAGLE-I hurricane data. This also allowed to develop the framework for simulation including identifying the agents and processes involved in restoration. A discussion of these three models is presented below.

3.5.1 Exponential Decay Function

As a first step, power outage recovery timelines were analyzed and parameterized for Hurricanes Irma, Harvey, Laura, Michael, and Zeta, which affected the states in the US Southeast region (Figure 2). The parameters were computed using an exponential decay relationship between the outage number (customers without power) at time *h* (denoted $N_i(h)$) and the time of peak outage $N_i(N_{0i})$ as discussed in Duffey (2019) [28]. The key features of Equation 1 include the maximum observed outage number (N_{0i}) (i.e., the number customers without power), the residual outage number representing outages remaining on the system after a long time (n_m), the number of hours since N_{0i} was observed (h), and the rate of restoration or restoration difficulty (β). The β parameter controls the shape of the exponential curve and quantifies restoration difficulty including varying degrees of damage, impassible roads, and lack of resources that may impede recovery operations. The most important parameter is restoration time, which is used to calculate other parameters using Equations 1 and 2.

$$\boldsymbol{N_i(h) = n_m + (N_{0i} - n_m) * e^{-\beta h}} \qquad [\boldsymbol{Eq.1}]$$

$$\boldsymbol{\beta = \ln\left(\frac{0.05 - \frac{1}{N_{0i}}}{1 - \frac{1}{N_{0i}}}\right) * \frac{-1}{H_{ETR}}} \qquad [\boldsymbol{Eq.2}]$$

Power outage restoration timelines can take many different shapes, depending upon the event and the type of damage. It is valuable to know both when a high percentage of all electric customers have their power restored and when outages attributable to a specific event have been restored. We computed two estimated time of restoration (ETR) parameters, ETR V1 and ETR V2. The first restoration threshold (ETR V1) is calculated as the time when the number of customers without power divided by the peak observed outage number (N_{0i}), and the second restoration threshold (ETR V2) is calculated as the number of remaining customers without power divided by the total number of electric customers served in the service area (Equations 3 and 4).

$$\boldsymbol{N_i(H_{ETR\,V1}) / N_{0i} \leq 5\%} \qquad [\boldsymbol{Eq.3}]$$

$$\boldsymbol{N_i(H_{ETR\,V2}) / N_{Total} \leq 5\%} \qquad [\boldsymbol{Eq.4}]$$

Because of both environmental conditions on utility distribution systems, as well as some measurement uncertainty in the EAGLE-I data, instead of computing ETRs for 99.3% of power outages restored from the peak, ETR V1 and ETR V2 were computed for 95% of outage restored from the peak outage. Equation 2 depicts the estimated time to restoration, H_{ETR}, that could be derived from restoration time profile parameters. By first using the ERT V1 and V2 calculated in Equations 3 and 4, two β parameters are then calculated based on the ETR V1 and ETR V2 respectively using Equation 2.

3.5.2 Multiple Linear Regression Model

To extend upon Equation 2, and since the parameters are easily interpretable and extended, a MLR model (Equation 3) was selected to examine the factors that contribute to the variation in β (difficulty in restoration). To create the model, the percentage of customers without power is primarily related to the natural logarithm of hours since the peak outage time. Each independent variable is evaluated with, and without, its interaction to the time component to represent its effect on the primary decay coefficient. The model was trained to minimize the total error across all time periods, using the "stats" package in R[1].

$$\hat{\boldsymbol{Y}} = \boldsymbol{\beta_0 t_0} + \boldsymbol{\beta_1 t_1} + \cdots + \boldsymbol{\beta_i t_i} + \boldsymbol{\beta_{i+1} t_{i+1}} \quad (3)$$

Based on existing literature, the following independent variables were used: population density of the county, maximum wind speed experienced, the amount of tree canopy in the region, land use/cover distribution, and peak outage experienced. Unlike the exponential decay function, this model was deployed for counties. To improve the model's accuracy, the training dataset was conservatively filtered to exclude counties that did not experience a significant outage due to the storm event. This was done by removing counties that did not experience outages greater than 0.05% of their total customer base.

3.5.3 Agent-Based Simulation Model

The ABM was developed to estimate a range of restoration times based on simulation, which could be used for decision-making and resource planning. Although, several tools and frameworks available for agent-based modeling, such as NetLogo, Repast, and MASON, these tools have proprietary coding language and environment. For our model, we used the open-source Mesa simulation package with Python [50], [51] that allows users to create ABMs using built-in core components (e.g., agent schedulers and spatial grids) or customized implementations; visualize them using a browser-based interface; analyze their results using Python's data analysis tools; and incorporate spatial representation of the environment for agent interaction.

Figure 5 depicts the conceptual framework of the ABM, and Table 2 lists the agents and their attributes used in the model. The model starts with information about the weather condition and future status, followed by the damage assessment agent that will provide damage status of the road networks and energy infrastructures contributing to both outage and restoration operation. Based on the outage information, the utility company will start identifying the components contributing to the outage (i.e., malfunctioning feeders, substations, or distribution lines). Upon receiving information from the weather and damage assessment agent, the utility company will gather available crews at the initial staging area and dispatch crews for repair tasks based on priority ranking preferences (e.g., customer numbers, critical service facilities). The city transportation agent, responsible for clearing of damaged road segments, will coordinate with utility companies to assist with dispatch of repair crew to specific substations based on accessible road networks. Each utility company is responsible for repair services within its service area based on priorities (e.g., critical assets, accessibility, damage to electrical components) until all the outages are restored.

[1] R Core Team. R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing (2021). https://www.R-project.org/.

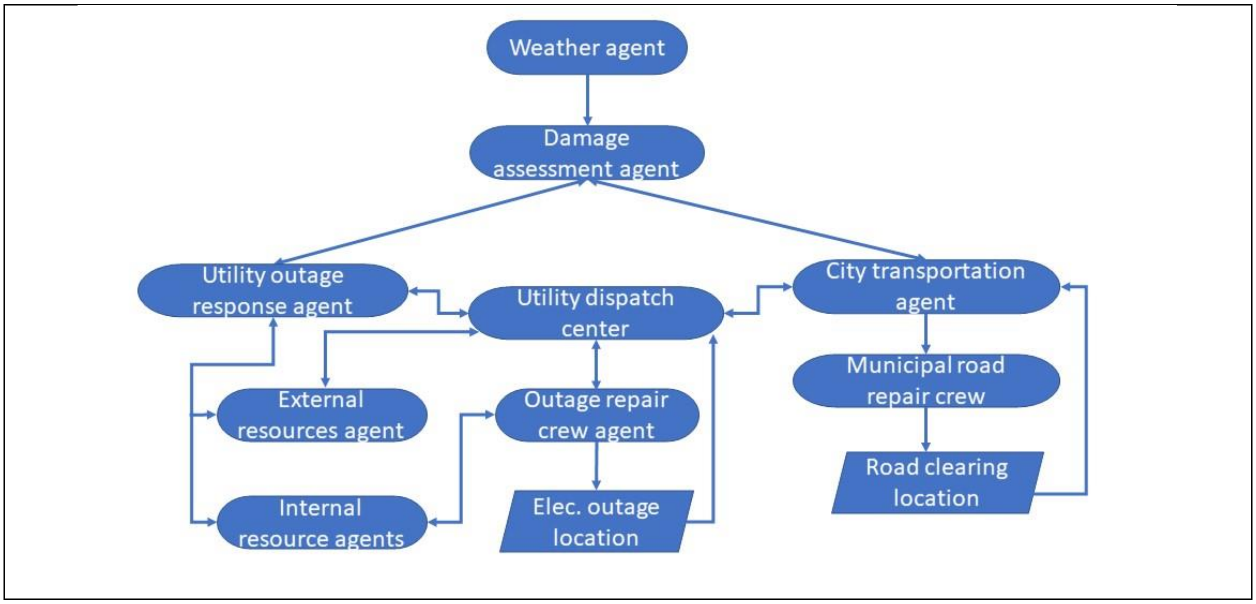


Figure 5: Conceptual framework and components of agent-based simulation model

Table 2: Detailed attributes and agent actions

Agent	Attributes	Main decisions
Weather agent	Severity level, temperature, wind, rain, moving path, duration	Update waiting time for repair. Feed info to damage agent.
Damage assessment agent	Influenced population number, damage/recovery level of energy infrastructure, road network	Update estimated recovery time. Feed info to outage and transportation agent.
Utility outage response agent	Number, location, cause, status, priority of current outages. Needed resource.	Update outage status. Feed info to resource agent and dispatch center. Report outage status to damage agent.
Utility dispatch center	Status of human resources, route accessibility, repair schedule, assigned crew for outage	Update repair schedule. Feed info to repair crew agent. Report outage status to outage agent.
City transportation agent	Status of road, repair locations, estimated travel time on road links	Update network status and repair schedule. Feed info to dispatch center. Report to damage agent
Internal resource agents	Location, number, of available internal personnel and equipment	Update available resource. Report to outage agent and dispatch center.
External resources agent	Location, number of available external personnel and equipment	Update available resource. Report to outage agent and dispatch center.
Outage repair crew agent	Current and next destination, travel time, shift schedule, estimated time on current outage	Update current status. Report to dispatch center. Request to resource agent
Municipal road repair crew	Current and next destination, travel time, shift schedule, next destination, estimated time on current outage	Update current status. Report to transportation agent.

The pseudocode of the restoration algorithm is presented in Table 3. Each repair crew team is treated as one agent, and each team may have at least two crew members. The two main repeated tasks in the simulation are routing request for repair crew agent and outage location assignment to repair crew agent. To address the large-scale simulation and routing in differing road conditions, we must both be able to modify the attributes of underlying roads as well as the behavior of the routing engine to avoid these damaged roads when possible. Because this sort of access and permission is restricted in other routing application programming interfaces (APIs) and engines such as Google Maps, we used pgRouting. In the current ABM deployment, the simulation ends when all substations experiencing outage are repaired.

Table 3. Pseudocode logic of each utility company in ABM simulation.

```
IF current time is not the estimated start time given by weather agent, wait
ELSE go into:
        Update current outage info from outage agent
        Update damage info from damage assessment agent
        Update current road info from transportation agent
        Update current resource info from resource agents
        While not all outages are fixed
        Segment the outage area based on workload, impacted customer
        Update priority list of the critical outage locations in each area
            For remaining outage areas
                Make/update shift schedule for each repair crew and team up
        Reassign/update each repair team to certain outage area
        Make/update dispatch schedule for each repair team based on priority/road
        Make/update the ramp and travel timetable for each repair team
        Report/update the outage cause, estimated repair time, required additional resource
        Report/update the estimated arrival time of personal or equipment if needed
        Update/report outage clearance and estimated start time for next outage
        Update the estimated restoration time for this area
Update the estimated finish time for whole restoration
```

4. RESULTS AND DISCUSSION

The current version of the distance decay, MLR and ABM allow us to capture the relationship between estimated restoration time and rate of restoration, the impact of independent variables as identified in literature on *ETR* and β, and the processes involved in restoration modeling. The results of these models are discussed in this section.

4.1 EXPONENTIAL DECAY FUNCTION

Figure 6 depicts the respective power outage restoration timelines for each hurricane event on a state-wide basis. The model equations, actual restoration times, and R^2 metrics measuring the goodness of fit between the observed outage count and exponential decay models are given in the bottom right corner of the figure. Among the five events, the predicted model (decay function) closely matches the raw outage count obtained from EAGLE-I for Hurricanes Michael and Irma. The models had an accuracy of 97.1% and 91.7% for these two events repectively, and V1 β values of 0.006 and 0.02. While restoration following Hurricane Michael was estimated to be 463 h, the restoration time for Hurricane Irma was estimated to be 151 h. The rate of restoration ranged from 0.013 to 0.026 for Hurricanes Harvey, Laura, and Zeta, and the estimated restoration time ranged from 71.25 h - 223.25 h. The model-estimated restoration time appears to be dependent on the event type and its impact on transmission vs. distribution system components, as was the case during Hurricane Laura. The uncertainties associated with the model are higher in the case of hurricanes with noisy outage data with a lot of spikes due to variation in outage at different time stamps. Figure 7**: Restoration constant distribution by county and utility service area** shows the distribution of β values for all storms aggregated by county or utility service area.

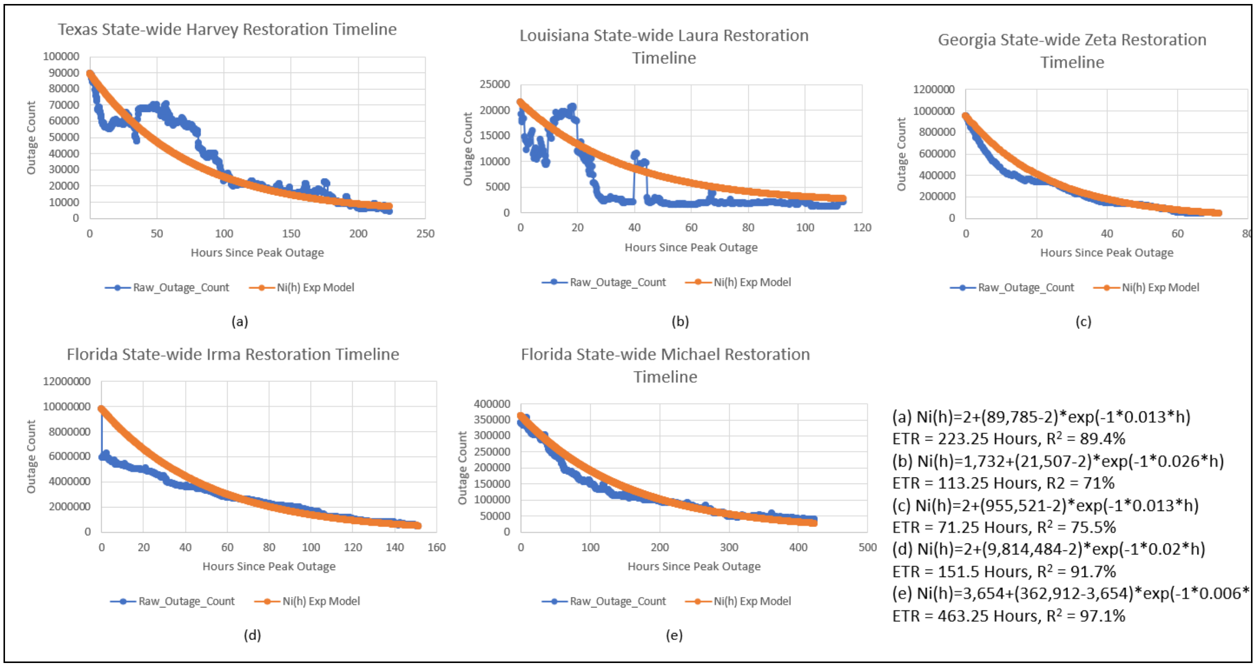


Figure 6: Hurricane power outage restoration timelines

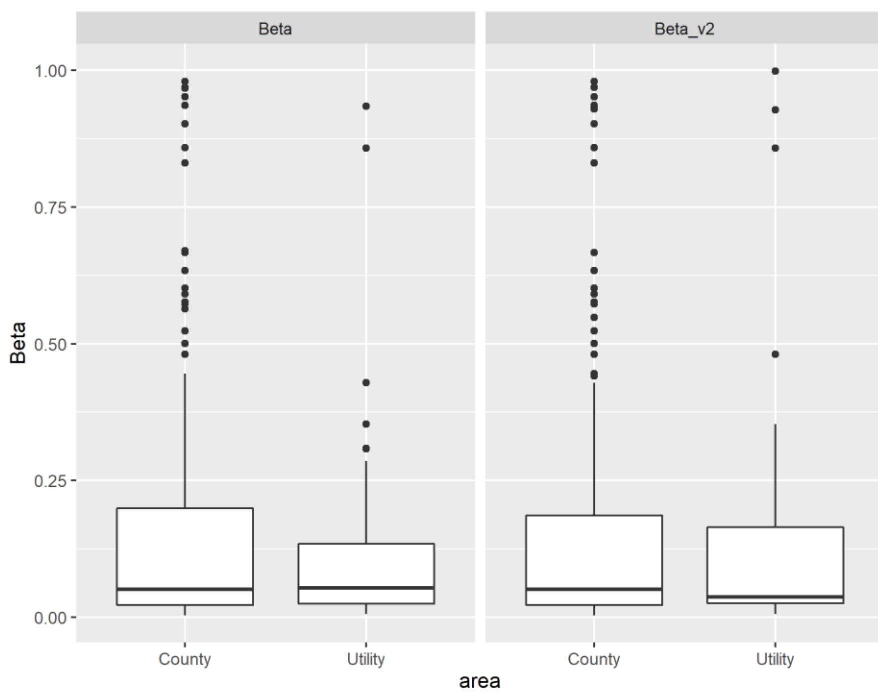


Figure 7: Restoration constant distribution by county and utility service area

4.2 MULTIPLE LINEAR REGRESSION MODEL

Table 4 displays the MLR coefficients and standard errors. To ensure the model's validity, potential variables were removed if they showed collinearity with other parameters and contributed little to overall model accuracy. In other words, single variable regression analyses were performed on each pair of input variables to ensure no two variables explained the same variation in the power outage data. Many variables (e.g., number of customers per substation) were analyzed and eliminated due to collinearities with the population density. This is not surprising because infrastructure in general tends to be correlated to areas with higher populations. Evidently, all estimates of coefficients were significant, but the overall best fit of the model across all storms (R^2) was approximately 0.4413, which is quite low. According to the model, more dense regions have better initial recovery times, while regions hit with higher wind speeds and featuring larger percentages of tree canopy and impermeable surfaces experience longer initial recovery times. The low R^2 values indicate that there are still large areas of unexplained interactions.

Table 4: MLR coefficients and standard errors

Parameter	Coefficient	Std. Error
(Intercept)	1.51E-01	1.05E-02
loghours	-2.29E-02	2.33E-03
log(density)	-6.73E-02	1.98E-03
windswath	1.11E-02	5.93E-03
canopy_percent	5.96E-03	8.41E-05
impervious_percent	2.29E-02	5.29E-04
loghours:log(density)	8.73E-03	4.36E-04
loghours:windswath	-1.85E-03	1.27E-03
loghours:canopy_percent	-1.04E-03	1.87E-05
loghours:impervious_percent	-3.68E-03	1.16E-04
R^2	0.4413	
Residual Standard Error	0.1802	

Figure 8 shows the distribution of actual vs. predicted estimated time of restoration for the five hurricane events. While data from all timesteps are incorporated, the primary intended use of the model is to predict the estimated time to restoration using the ETR V1 methodology. Overall, the model overestimates the actual time to restoration. The notable exception is Hurricane Harvey, where there are both overpredictions and underpredictions. This likely is due to the model's focus on wind speed effects rather than precipitation, as flooding was the primary cause of damage in Hurricane Harvey. The two major limitations of the MLR model in the current version are: (1) the distribution of errors across storm events implies the model does not capture the nature of each event, and (2) the presence of unrealistic predictions, such as an outage count below 0 or greater than the total number of customers. Errors from these predictions can skew the model during different time periods and are likely a factor in the tendency to overpredict ETR. As the purpose of this pilot implementation was to develop the MLR model, future improvements will focus on tuning the model to have more accurate predictions in the time of interest by adding weight factors to the model based on the time period as well as event conditions to reduce error.

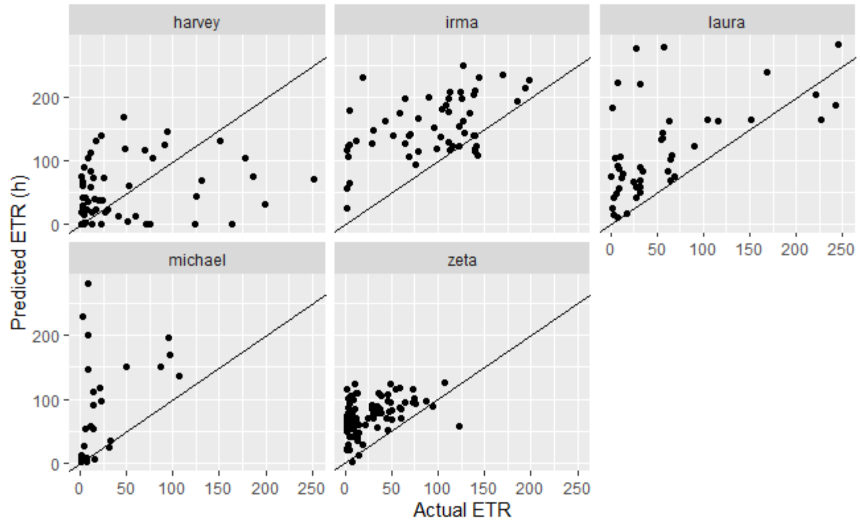


Figure 8: Comparison of actual vs. estimated restoration time (ETR V1) for five hurricanes

4.3 AGENT BASED SIMULATION MODEL

The current ABM estimates restoration time for each county in Florida and assumes that outages are occurring at the substation level such that the restoration will progress once all impacted substations are repaired. For visualization purposes, orange dots represent functional substations, red dots represent substations with outages, blue dots represent outage repair crew teams, green dots represent the presence of repair crews to repair the outages. Figure 9a displays the attributes of substations (e.g., id, location in coordinates, number of households being served, location county, etc.), and Figure 9b lists the attributes of the outage repair crew team (e.g., travel or idle status, travel speed), which could be altered by users to generate a range of *ETR*.

Figure 10 illustrates the initialization of the simulation with the repair crews gathered at the initial staging area. At each timestep, the location of the outage repair crew is interpolated based on its routing to the destination. The simulation stops when all outages are repaired. The following assumptions were made in this current version, and each simulation was run five times.

i. From the total of 3,000 substations in Florida, the substation numbers with outages were randomized at four levels [100, 500, 1,000, 1,500].

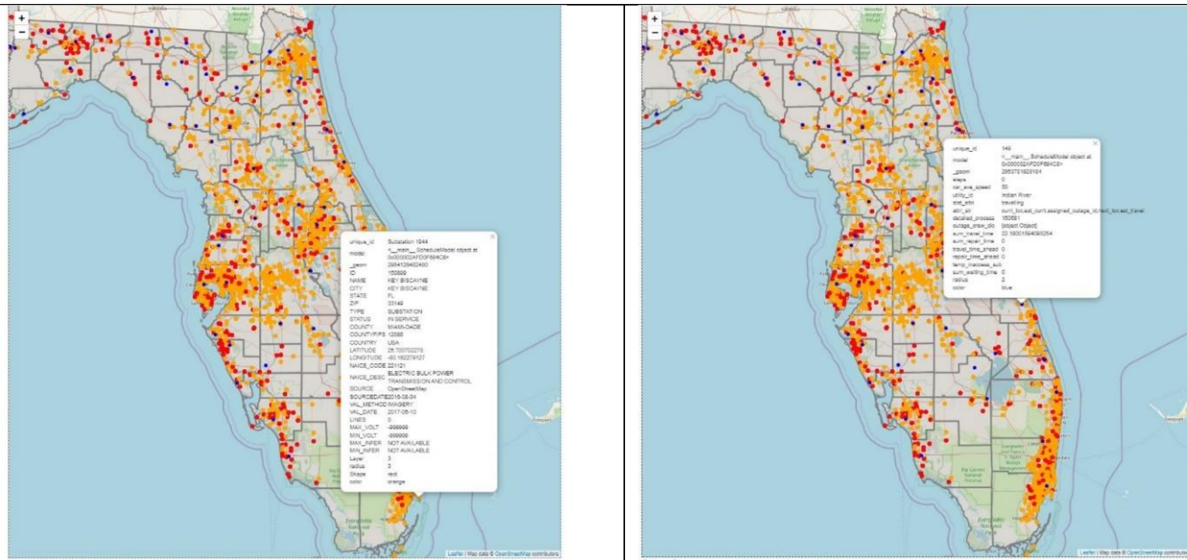
ii. The repair time of substation is randomized uniformly between 1 and 2 hours.

iii. The household attached to each substation is a random number ranging from 1,000 to 10,000.

iv. Each utility company/county is assumed to have the same number of outage repair crew teams, and this number is randomized at four levels [5, 15, 25, 35].

v. Each simulation timestep is set to 1 h. Note that this timestep setting (1 min, 1 hour, or 2 hour) does not impact the results, and the small timestep provides more details with more computational effort.

vi. When road damage is considered, the number of damaged road segments is set to 500, which are randomly selected, and the repair time of damaged road segment is randomized uniformly between 1 and 24 hours.



(a) (b)

Figure 9:Substation attributes (a) and repair crew attributes (b)

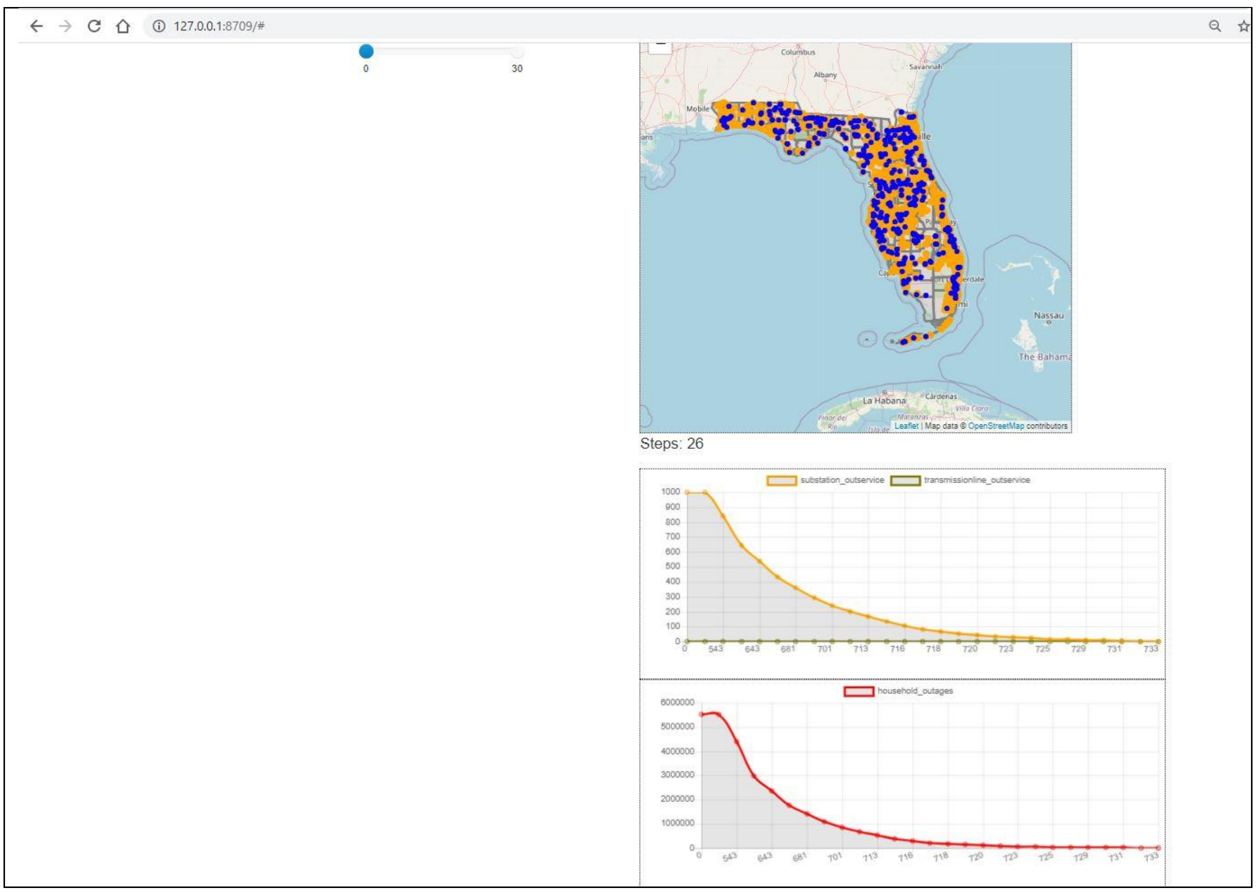


Figure 10:Visualization of the ABM tool and simulated ETR for Florida. The top figure depicts the geospatial distribution of substations to be restored during a hypothetical tropical storm event. The middle figure plots the substations being restored (X-axis - time to restore, and Y-axis - number of substations being restored). The bottom figure plots the time to restore all impacted customers (residential households) (X-axis – time to restore, and Y-axis - number of households being restored).

5. CONCLUSION AND FUTURE DIRECTION

Evidently, the current version of the decay function was able to capture the following two parameters - estimated restoration time and rate of restoration that are essential for resource planning at both county and utility service area level. The MLR model was able to identify the variables contributing to the restoration time. However, the performance of both the decay function and MLR are influenced by the event type, outage extent, impacted area, population density and base customer level. For instance, while the decay function performed well in terms of computing *ETR* and β (with high accuracy >90% based on R^2) in case of wide-area large scale outages, the model performed poorly in the case of events with fluctuating outages due to continuous disruptions to the system over a period (e.g., the conditions during Hurricane Laura). A similar trend was observed in the MLR model, and the model did not identify counties and utility service areas where restoration would take longer depending upon the underlying impacts, base customer, county type and extent of damage. The operational ABM can simulate agent activities and restoration progress using hypothetical event and county level outages.

In their current versions, the three models developed can capture the variables, their relationships, and the processes that need to be undertaken to estimate restoration time and rate of restoration. Because the current scope of the models was to forecast restoration time in case tropical storm events, future work will focus on (1) incorporating Category I and II tropical storm events with fluctuating outages; (2) fine-tuning the decay function and MLR models to compute a range of *ETR* and β values for different category storm events based on population density, outage extent, damage, and land use/cover distribution (specifically, vegetation); (3) operationalizing ABM using real events, (4) validating and calibrating the probabilistic models and ABM, and (5) expanding the models to winter storm events. We will build on the relationships with utilities (EPB Chattanooga and Knoxville Utility Board) and NRECA (National Rural Electric Cooperation Association) to obtain access to restoration datasets for verification, validation, and calibration of the models, and the restoration plan for verification of the ABM model components. We will develop an initial integration plan to integrate the model outputs into the EAGLE-I platform to provide situational awareness information about restoration to DOE policy makers and first responders.

6. REFERENCES

[1] Cybersecurity and Infrastructure Security Agency, US Department of Homeland Security (DHS). 2021. “Energy Sector.” DHS Critical Infrastructure Sectors. [Online]. Available at: https://www.cisa.gov/energy-sector. [Accessed January 12, 2022].

[2] DHS. 2021. “Joint National Priorities for Critical Infrastructure Security and Resilience.” DHS. [Online]. Available at: https://www.dhs.gov/sites/default/files/publications/JointNationalPrioritiesFactSheet-508.pdf. [Accessed January 12, 2022].

[3] McKinsey Global Institute. 2020. “Climate Risk and Response: Physical Hazard and Socioeconomic Impacts – Will Infrastructure Bend or Break under Climate Stress.” McKinsey Global Institute [Online]. Available at: https://www.mckinsey.com/~/media/mckinsey/business%20functions/sustainability/our%20insights/will%20infrastructure%20bend%20or%20break%20under%20climate%20stress/will-infrastructure-bend-or-break-under-climate-stress-case-study-old.pdf. [Accessed January 12, 2022].

[4] National Aeronautics and Space Administration (NASA) Global Earth Observatory. 2018. “Night Lights Show Slow Recovery of Maria.” NASA [Online]. Available at: https://earthobservatory.nasa.gov/images/144371/night-lights-show-slow-recovery-from-maria. [Accessed January 12, 2022].

[5] Campbell, A. F. 2018. "It Took 11 Months to Restore Power to Puerto Rico After Hurricane Maria. A Similar Crisis Could Happen Again." Vox [Online]. Available at: https://www.vox.com/identities/2018/8/15/17692414/puerto-rico-power-electricity-restored-hurricane-maria. [Accessed January 12, 2022].

[6] Mazzei, P. 2021. "Why Don't We Have Electricity?: Outages Plague Puerto Rico." *New York Times* [Online]. Available at: https://www.nytimes.com/2021/10/19/us/puerto-rico-electricity-protest.html. [Accessed January 12, 2022].

[7] Schuppe, J. 2021. "Hurricane Ida Power Grid Failure Forces a Reckoning Over Entergy's Monopoly In The South." NBCNews [Online]. Available at: https://www.nbcnews.com/news/us-news/hurricane-ida-power-grid-failure-forces-reckoning-over-entergy-s-n1279971. [Accessed January 12, 2022].

[8] Energy Information Administration (EIA). 2021. "Hurricane Ida Caused At Least 1.2 Million Electricity Customers to Lose Power." EIA [Online]. Available at: https://www.eia.gov/todayinenergy/detail.php?id=49556. [Accessed January 12, 2022].

[9] Busby, J. W., Baker, K., Bazilian, M. D., Gilbert, A. Q., Grubert, E., Rai, V., Rhodes, J. D., Shidore, S., Smith, C. A., Webber, M. E. 2021. "Cascading Risks: Understanding the 2021 Winter Blackout in Texas." *Energy Research & Social Science* 77 (102106). https://doi.org/10.1016/j.erss.2021.102106.

[10] University of Houston. 2021. "The Winter Storm of 2021." University of Houston [Online]. Available at: https://uh.edu/hobby/winter2021/storm.pdf. [Accessed January 12, 2022].

[11] Wang, Z., Hong, T., and Li, H. 2021. "Informing the Planning of Rotating Power Outages in Heat Waves Through Data Analytics of Connected Smart Thermostats for Residential Buildings." *Environmental Research Letters* 16. https://doi.org/10.1088/1748-9326/ac092f.

[12] Zanocco, C., Flora, J., Rajagopal, R., Boudet, H. 2021. "When the Lights Go Out: Californians' Experience with Wildfire-related Public Safety Power Shutoffs Increases Intention to Adopt Solar and Storage." *Energy Research & Social Science* 79 (102183). https://doi.org/10.1016/j.erss.2021.102183.

[13] EIA. 2021. "U.S. Electricity Customers Experienced Eight Hours of Power Interruptions in 2020." EIA [Online]. Available at: https://www.eia.gov/todayinenergy/detail.php?id=50316 [Accessed January 24, 2022].

[14] The White House. 2021. "FactSheet: The Bipartisan Infrastructure Deal." The White House [Online]. Available at: https://www.whitehouse.gov/briefing-room/statements-releases/2021/11/06/fact-sheet-the-bipartisan-infrastructure-deal/. [Accessed January 12, 2022].

[15] Hauser, C., and Sandoval, E. 2021. "Death Toll from Texas Winter Storm Continues to Rise." *New York Times* [Online]. Available at: https://www.nytimes.com/2021/07/14/us/texas-winter-stormdeaths.html. [Accessed January 12, 2022].

[16] Garcia, A. 2021. "Winter Storm Uri Cost Texas between $80 and $130 billion." CHRON [Online]. Available at: https://www.chron.com/politics/article/Texas-winter-storm-freeze-deaths-financial-cost-16585329.php. [Accessed January 12, 2022].

[17] National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information. 2021. "U.S. Billion-Dollar Weather and Climate Disasters (2021)." NOAA [Online]. Available at: https://www.ncdc.noaa.gov/billions/. DOI: 10.25921/stkw-7w73.

[18] Climate Central. 2020. "Power Off: Extreme Weather and Power Outages." Climate Central [Online]. Available at: https://medialibrary.climatecentral.org/resources/power-outages. [Accessed January 12, 2022].

[19] Qiu, F., and Li, P. 2017. "An Integrated Approach for Power System Restoration Planning." *Proceedings of the EEE* 105(7): 1234–1252.

[20] American Public Power Association (APPA). 2018. "Restoration Best Practices Guidebook." APPA [Online]. Available at: https://www.publicpower.org/resource/restoration-best-practices-guidebook. [Accessed January 12, 2022].

[21] Link, L. H., Liou, K.-L., and Liu, C-C. 1995. "From Generic Restoration Actions to Specific Restoration Strategies." *IEEE Transactions on Power Systems* 10(2): 745–752.

[22] Chow, M.-Y., Taylor, L. S., Chow, M.-S. 1996. "Time of Outage Restoration Analysis in Distribution Systems." *IEEE Transactions on Power Delivery* 11(3): 1652–1658.

[23] Executive Office of the President. 2013. *Economic Benefits of Increasing Electric Grid Resilience to Weather Outages–Technical Report* [Online]. Available at: https://www.energy.gov/sites/prod/files/2013/08/f2/Grid%20Resiliency%20Report_FINAL.pdf. [Accessed January 12, 2022].

[24] Davidson, R. A., Liu, H., and Apanasovich, T. V. 2017. "Estimation of Post-Storm Restoration Times for Electric Power Distribution Systems." *Advances in Electric Power and Energy Systems*. Hoboken, NJ: John Wiley & Sons Ltd, pp. 251–284. https://doi.org/10.1002/9781119260295.ch7.

[25] Nateghi, R., Guikema, S. D., Quiring, S. M. 2011. "Comparison and Validation of Statistical Methods for Predicting Power Outage Durations in the Event of Hurricanes." *Risk Analysis* 31 (12): 1897–1906. https://doi.org/10.1111/j.1539-6924.2011.01618.x.

[26] Duffey, R. B., and Ha, T. 2013. "The Probability and Timing of Power System Restoration." *IEEE Transactions on Power Systems* 28 (1): 3–9. DOI:10.1109/TPWRS.2012.2203832.

[27] Duffey, R. B. 2019. "Power Restoration Prediction Following Extreme Events and Disasters." *International Journal of Disaster Risk Science* 10: 134–148. https://doi.org/10.1007/s13753-018-0189-2.

[28] Walsh, T., Layton, T., Wanik, D., and Mellor, J. 2018. "Agent Based Model to Estimate Time to Restoration of Storm-Induced Power Outages." *Infrastructures* 3 (33): 1–21.

[29] Çağnan, Z., Davidson, R. A., and Guikema, S. D. 2006. "Post-Earthquake Restoration Planning for Los Angeles Electric Power." *Earthquake Spectra* 22 (3): 589–608. doi:10.1193/1.2222400.

[30] Kunlong, S., Jianming, J., Zongbao, G., Gongyi, S., and Yue, L. 2019. "An Innovative Method for Optimization of Power System Restoration Path." In *Proceedings of the 2019 Chinese Control and Decision Conference (CCDC)*, pp. 4225–4230. DOI: 10.1109/CCDC.2019.8833265.

[31] Anmar, A., Ma., S., Wang, Z., Wang, J., Ryan, S. M., and Chen, C. "Optimizing Service Restoration in Distribution Systems with Uncertain Repair Time and Demand." *IEEE Transactions on Power Systems* 33 (6). DOI:10.1109/TPWRS.2018.2855102.

[32] Chen, Z., Geng, L., Lan, X., and Mei, J. 2020. "Intelligent Power Grid Outage Plan Optimization Decision Method based on Flexible Modeling of Outage Rule Set." *AIP Conference Proceedings* 2238: 020026. https://doi.org/10.1063/5.0011659.

[33] National Academies of Sciences, Engineering, and Medicine 2017. *Enhancing the Resilience of the Nation's Electricity System*. Washington, DC: The National Academies Press. https://doi.org/10.17226/24836.

[34] Kar, B., Bobeck, J., Moss, T., and Hughes, D. 2021. "Spatiotemporal Tracking of Wide Area Power Outage from Night-Time Light Imagery." In *Proceedings of the 2021 IGARSS.* DOI: 10.1109/IGARSS47720.2021.9554293.

[35] Kar, B., Brewer, J., Omitaomu, O. A., Iyengar, A., Roberts, N. and Hoesly. R. 2021. "Accessibility and Availability of Gas Stations for Liquid Fuel Supply During Severe Weather Events." In *Proceedings of the 2021 IISE Annual Conference*, pp. 722–728.

[36] Kar, B., and Ethridge, J. 2019. "Mobility Pattern Analysis for Recovery and Restoration Activities Using Geo-Tagged Tweets." In *Proceedings of Second ACM SIGSPATIAL International Workshop on Advancements in Resilient and Intelligent Cities.* 10.1145/3356395.3365547.

[37] National Hurricane Center (NHC). 2021. "Tropical Cyclone Climatology." NOAA [Online]. Available at: https://www.nhc.noaa.gov/climo/. [Accessed January 12, 2022].

[38] National Weather Service. "Hurricane Irma – September 10th, 2017." [Online]. Available: https://www.weather.gov/mfl/hurricaneirma. [Accessed August 2021].

[39] Energy Information Administration (EIA). 2021. "Hurricane Irma Cut Power to Nearly Two-thirds of Florida's Electricity Customers." EIA [Online]. Available at: https://www.eia.gov/todayinenergy/detail.php?id=32992. [Accessed January 12, 2022].

[40] NHC. "Hurricane Michael Wind Swath." NHC [Online]. Updated March 9, 2019. Available: https://www.arcgis.com/home/item.html?id=433fdd370e9046a8bb085924f7617874. [Accessed August 2021].

[41] Florida Public ervice Commission. "Hurricane Outage Reports." [Online]. Available: http://www.psc.state.fl.us/Home/HurricaneReport. [Accessed August 2021]

[42] National Weather Service. "Hurricane Harvey and Its Impacts on Southeast Texas (August 25–29, 2017)." [Online]. Available: https://www.weather.gov/hgx/hurricaneharvey. [Accessed January 12, 2022].

[43] EIA. "Hurricane Harvey Caused Electric System Outages and Affected Wind Generation in Texas." September 13, 2017 [Online]. Avalilable at: https://www.eia.gov/todayinenergy/detail.php?id=32892. [Accessed January 12, 2022].

[44] National Weather Service. "Hurricane Laura (August 20–29, 2020)." [Online]. Available: https://www.weather.gov/lch/2020Laura. [Accessed January 12, 2022].

[45] EIA. "Hurricane Laura Shut in More Gulf of Mexico Crude Oil Production than Any Storm since 2008." October 2, 2020 [Online]. Avalilable at: https://www.eia.gov/todayinenergy/detail.php?id=45376. [Accessed January 12, 2022].

[46] Entergy, "Entergy Provides Update on Hurricane Laura." September 22, 2020 [Online]. Available at: https://www.entergynewsroom.com/news/entergy-provides-update-on-hurricane-laura. [Accessed January 12, 2022].

[47] NHC. 2021, May 10. "*Hurricane Zeta*." NHC Tropical Cyclone Report. [Online]. Available: https://www.nhc.noaa.gov/data/tcr/AL282020_Zeta.pdf. [Accessed January 12, 2022].

[48] Masers, J. 2020. "Hurricane Zeta's High Winds Cause Second Largest U.S. Power Outage of 2020." Yale Climate Connections [Online]. Available: https://yaleclimateconnections.org/2020/10/hurricane-zetas-high-winds-cause-largest-u-s-power-outage-of-2020/. [Accessed January 12, 2022].

[49] Kar, B., & Hodgson, M. E. (2012a). Relationship Between Observational Scale and Modeled Potential Residential Loss From a Storm Surge. *GISRS*, 202-227.

[50] Masad, D., and Kazil, J. 2015. "Mesa: An Agent-Based Modeling Framework." In Proceedings of the Fourteenth Python in Science Conference (SCIPY 2015), pp. 53–60.

[51] Kazil, J., Masad, D., and Crooks, A. 2020. "Utilizing Python for Agent-Based Modeling: The Mesa Framework." In Thomson, R., Bisgin, H., Dancy, C., Hyder, A., and Hussain, M., eds. *Social, Cultural, and Behavioral Modeling*. Springer, pp. 308–317.