# Routing Optimization for Storm Damage Assessment

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***Abstract*— Significant damages caused by extreme weather conditions such as flood, storm, hurricanes, blizzards etc., contribute multiple and widely-spread damages to electric power transmission and distribution systems resulting in large-scale power failures. In such cases, the electric utilities send repair crew to affected locations as soon as possible to repair the transmission and distribution systems. Damage assessment process is one of the steps in system restoration process, which assesses overall damage and gives out an approximate restoration time for the damaged location. A systematic method of the damage assessment procedure is proposed in an effort to reduce the restoration time in conjunction with drone technology, which offers potential to make the restoration process efficient and safe. A routing algorithm that provides a path covering the entire part of damaged area of a circuit. Detailed procedure is illustrated on a real distribution network as a case study.**

***Keywords—power restoration, damage assessment, rural postman problem***

## I. INTRODUCTION

High impact low frequency (HILF) events such as hurricanes, ice storms, blizzards, and high-speed winds cause heavy damage to electrical transmission and distribution grid. For example, Hurricane Irma damaged the entire power system of the U.S. Virgin Islands in September 2017, which resulted in 20,000 residents to stay without power [1]. In addition, Hurricane Maria in October 2017 devastated Puerto Rico's electrical system into pieces. Duke Energy workers have been working to restore power in Puerto Rico since January 2018 [2]. When there is no power, people suffer from absence of various resources. So, it is very crucial to restore the power distribution system as soon as possible to regain power to all customers.

Restoration of electrical services after HILF events is a multiple step process with different personnel and resources deployed. The restoration procedure can be divided into three sequential phases: 1) before the storm, 2) during the storm, and 3) after the storm. Each phase has different tasks to accomplish as described in the following [3].

In the before the storm phase, weather forecasts are collected from various prediction models. When utilities foresee any potential damage to the grid from the forecasts, they prepare for the storm with material procurement and staffing crew members. Sometimes utilities ask for support from neighboring utilities if they do not have enough resources to cope with severe expected damage.

During the storm, a utility coordinator looks at resources and decides on the roles of internal and external crews. Most restoration crews remain on standby while only emergency restoration is performed such as hospitals, and prisons. Outage reports are accumulated and documented in this phase.

After the storm, the first step of the restoration process is to assess damages and estimate the amount of material and crew resources needed to restore power to customers. A damage assessor is deployed to the part of a circuit (or the entire circuit), where outage has occurred, to inspect the distribution lines. As damages are being assessed, damage information is transmitted to the coordinator, who dispatches available restoration crews and assign materials.

Recently, unmanned aerial vehicles have been used in energy industry to inspect solar panels, wind turbines, transmission lines and other structures. For example, Duke Energy uses drones with a thermal imaging device that identifies faults in solar panels. In addition to solar plants, they use drones to assess storm damage, to inspect towering equipment, and to track construction from beginning to end. Duke Energy was one of the first operators in the United States to use drone technology in power restoration by using drones in Puerto Rico after Hurricane Maria in October 2017 [4]. Drones help crewmembers find damages such as broken poles, downed power lines in densely vegetated areas, and to uncover safe paths for crew members in hazardous areas.

Observing the potential benefit of utilizing drone technology in the context of a power restoration process, we study a systematic damage assessment operation by proposing a drone routing algorithm that provides a drone path covering the entire part of the circuit under consideration. If the drone routing algorithm is effectively integrated in a damage assessment process, it is expected to make restoration process much faster and efficient.

## II. LITERATURE REVIEW

Restoration of electrical services is a multiple step process for a utility to restore the power as quick as possible when a HILF event occurs. Considering post-earthquake electric power restoration tasks, Xu et al. [5] propose a stochastic integer program, which minimizes the average time of customer without power. Their model determines how to schedule inspection, damage assessment, and repair tasks in the post-earthquake restoration of the electric power system. In the initial phase, operators inspect the generation stations and substations, while

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priority is given to substations that are closer to the epicenter of the earthquake. In the second phase, Damage Assessment Teams (DATs) are dispatched to damaged substations. In the third phase, repair teams are dispatched from operation centers to the damaged substations that have been assessed by DATs.

The effectiveness of the schedules generated by solving their optimization model is evaluated via a discrete event simulation study of the restoration process, and is compared with that of the schedules practiced by the power company. They used three measures for comparison: average time without power, time required to restore 90% of customers, and time required to restore 98% of customers. Strategies like restoration time for the first customers and outage duration for the last customers are more effective than current restoration process. This model is applied to the Los Angeles Department of Water and Power electric power system.

Liu at al. [6] propose accelerated failure time (AFT) models to estimate the duration of each electric power outage after a storm. The proposed model is a type of survival analysis model, which is built using a dataset about six hurricanes and eight ice storms. AFT models predict the duration of possible outage, and by aggregating estimated outage durations and accounting for variable outage start times, restoration times are estimated. The proposed technique can be applied as storm approaches, before damage assessment process begins, which helps utility inform expected power restoration time to affected customers. This model was applied to hurricane and ice storm events for three major electric power companies on the East Coast of United States. The key limitation of this approach is data availability, by the nature of HILF events.

Nateghi [7] compares the accuracy of predicted power outage duration of five distinct statistical methods. Analysis is based on a dataset containing power outage durations caused by Hurricane Ivan in 2004. Two survival analysis models together with three data mining techniques were implemented to compare the predictive accuracy. These methods are AFT regression, Cox proportional hazard (CPH) regression, classification and regression trees (CART), multivariate adaptive regression splines (MARS), and Bayesian additive regression trees (BART). Through different validation tests, they conclude that the BART-based forecast model offers the most accurate estimates of power outage durations.

Nateghi et al. [8] propose a predictive model, using the method of random forests to forecast duration of power outage prior to hurricane landfall. They attribute long power outage durations to the climatic and geographic characteristics of the service area. The results indicate that the proposed random forecast model predicts outage restoration times with an improved accuracy over existing models. For example, the model is 87 % more accurate than the BART model used by Nateghi [7] on basis of Mean Absolute Error.

Kozin and Zhou [9] proposed a model for a lifeline-restoration process after earthquake, based on a discrete-state, discrete-time Markov process. In this lifeline system electricity, water, transportation, railway, and telephone services are considered. The basic principle behind the proposed model is to assign limited resources to different lifelines and minimize total loss, which is caused by damaged lifeline systems. The formulation of damage restoration process of lifeline systems considers two factors 1) initial damage probability state and 2) economic return. To optimize the limited resources that maximize the economic return from lifeline functioning, dynamic programming is used.

Nojima and Kameda [10] proposed a procedure to maximize efficiency of overall restoration process using the graph theory and optimization theory. In this paper, the restoration of lifeline network systems is executed in two stages: the first stage extracts tree structures from the network and the second stage determines the repair sequence of damaged network in the tree structure. Horn's algorithm [11] is used to determine the optimal repair sequence. Three types of tree structures such as minimum spanning tree, shortest path tree, and approximately optimum tree are used to find better connectivity of network. Among these minimum spanning trees are found to be the most efficient tree structure in a majority of cases.

Noda [12] proposes a method that uses a neural network to minimize the likelihood of functional loss to a telephone system. The neural network provides a repair sequencing of damaged facilities to determine restoration process. Wang et al. [13] propose a depot location model that efficiently manages the resources that are needed for restoration. The problem is addressed in two phases: (1) minimize total transportation cost – how to locate repair depots and transport required resources from each depot to damaged locations, and (2) determine how additional repair depots would help to minimize total cost (restoration time).

Wu et al. [14] propose a fuzzy based approach to present a repair schedule of crew and vehicle routing during various kinds of outages. Their model determines repair priorities of crews and vehicles for effective dispatch to damaged locations. The model is implemented in the Taiwan-power company through of their Outage Management System.

## III. Model Description

This section presents a drone routing algorithm that provides a drone path covering the entire part of the distribution network. The algorithm aims to find the shortest (or minimal-distance) path such that all lines of the power distribution network experiencing outage are covered by the path. Consider a connected network $G(V, E)$ with a set of edges E and a set of vertices V where each edge $(i, j) \in E$ has a nonnegative distance $C_{(i,j)}$. The idea of the proposed algorithm is to augment G to a unicursal (a.k.a., Eulerian) network $G'(V, E')$, where $E'$ is a super set of $E$. $E'$ is constructed by adding a set of edges obtained from minimum-distance matching for the complete network consisting of only odd degree vertices. Then, an Eulerian tour of $G'$ results in a drone path.

To materialize this idea, we propose the following drone-path algorithm, which consists of three phases. Phase I is to extract the odd degree vertices from the network G. Phase II finds a solution to the minimum-distance matching problem of a complete network constructed with odd degree vertices using binary integer programming to obtain an Eulerian network. Phase III finds an Eulerian tour for the resulting network from Phase II. The overall procedure is presented in what follows.

## A. Phase I: Extraction of Odd Vertices

In this phase, from a given power distribution network $G(V, E)$, all odd degree vertices are extracted. Let *the vertex-edge incidence matrix* $(a_{ve})$, $v \in V$ and $e \in E$, defined by

$$a_{ve} = \begin{cases} 1 & \text{if } e \text{ and } v \text{ are incident} \\ 0 & \text{otherwise.} \end{cases}$$

The sum $\sum_e a_{ve}$ represents the degree of vertex $v$. Let $b_v$ be a binary value given by

$$b_v \equiv \sum_{e \in E} a_{ve} \pmod 2,$$

where *mod* denotes modulo operation. Thus, $b_v$ is zero when the degree of vertex $v$ is even and one when the degree of vertex $v$ is odd. Define $\overline{V} \equiv \{v \in V: b_v=1\}$. That is,

$\overline{V} \subset V$ is the set of odd vertices of the network $G$. Note that $|\overline{V}|$ is an even number, where $|\cdot|$ denotes set cardinality.

## B. Phase II: Minimum-Distance Matching

Consider an undirected complete network $\overline{G}(\overline{V}, \overline{E})$. In this phase, a minimum-distance matching in the network $\overline{G}$ is obtained. A minimum distance matching is a pairing of vertices such that each vertex is paired with exactly one other vertex so that the total distance of the edges connecting the pairs is minimized. A binary integer programming model to find a minimum-distance matching is presented below. Let $\bar{C}_{(i,j)}$ denote the distance of edge $(i, j) \in \bar{E}$ and $x_{(i,j)}$ be a binary variable that represents pairing of $i$ and $j$ (1 if paired, 0 otherwise).

Minimize $\quad \sum_{(i,j)\in E} \bar{C}_{(i,j)}\, x_{(i,j)} \qquad (1)$

Subject to $\quad \sum_{j \in \overline{V} \setminus \{i\}} x_{(i,j)} = 1 \qquad \forall\, i \in \bar{V} \qquad (2)$

$\quad x_{(i,j)} \in \{0,1\} \qquad \forall\, (i,j) \in \bar{E} \qquad (3)$

The objective function (1) minimizes the total distance of matching. Constraints (2) and (3) ensure that each vertex is paired with only one other vertex.

Let $\hat{E}$ denote the set of edges obtained from the minimum-distance matching. Then we construct a unicursal network $G'(V, E')$, where $E'$ is the disjoint union of $E$ and $\hat{E}$.

## C. Phase III: Eulerian Tour

Once a unicursal network $G'(V, E')$ has been obtained, an Eulerian cycle on $G'$ can be found using existing algorithms such as Fleury's algorithm or Hierholzer's algorithm. Hierholzer's algorithm works similar to Fleury's algorithm, but it is used for directed network. Since network $G'$ is an undirected network, the Fleury's algorithm will be employed to find an Eulerian cycle. To explain how the Fleury's algorithm proceeds, there is a need for defining two terminologies; *bridge* and *non-bridge edge*. An edge is said to be a bridge, if removing it results in a disconnected network. Similarly, an edge is a non-bridge, if it does not disconnect the network when it is deleted. The basic principle of the Fleury's algorithm is to follow edges one at a time while always choosing a non-bridge if possible.

The steps of the Fleury's algorithm can be summarized as follows:

Step 1: Given $G'(V, E')$, select $i \in V$, and initialize a sequence $S = \{i\}$.
Step 2: If $E' = \emptyset$, stop, with $S$. Otherwise, go to Step 3.
Step 3: Let $V_i = \{ j \in V: (i,j) \text{ is incident at } i \}$.
Step 4: Select $k \in V_i$. If $(i, k)$ is a non-bridge or $|V_i| = 1$, then go to step 5. Otherwise, update $V_i \leftarrow V_i \setminus \{ k \}$ and repeat step 4.
Step 5: Update $E' \leftarrow E' \setminus \{(i, k)\}$, add $k$ to $S$, and let $i \leftarrow k$, and return to step 2.

From above steps, an Eulerian tour is constructed on $G'$.

Once a drone path is obtained, flight plan is downloaded into the drone controller to inspect the given network. Since drones are battery operated, flight times are limited by battery capacities. For example, as assumed later in Section IV, consider maximum flight of 16 minutes and average speed of 7 miles/hour of the DJI Phantom [15], which results a total flight distance of 1.8 miles. If the distance of the flight path is too long, the battery has to be replaced at certain points of the path. Let max_dist denote the maximum distance that a drone can fly with a fully charged battery.

Step 1: Initialize $i = 2$, $dis = 0$, and $BR = \{\}$.
Step 2: If $i > K$ then stop with $BR$, Otherwise,

$$dist \leftarrow dist + C_{(v_{(i-1)}, v_{(i)})}.$$

Step3: If $dist > max\_dist$, the add $v_{(i-1)}$ to BR, reset dist =0, and return to Step 2, Otherwise, go to Step 4.
Step 4: $i \leftarrow i + 1$. Return to step 2.

The resulting BR represents the set of battery replacement vertices.

# IV. Case Study

To demonstrate its application in a realistic setting, the drone routing algorithm is applied to a real feeder network. The input data is composed of vertices and their corresponding $(x, y)$ coordinates, and edges that correspond to power lines. The network used in this case-study consists of 248 vertices and 248 edges. This feeder is referred to as 'Kudzu' (Fig. 1). The total distance of all edges in the Kudzu network is 58,254 feet. Each

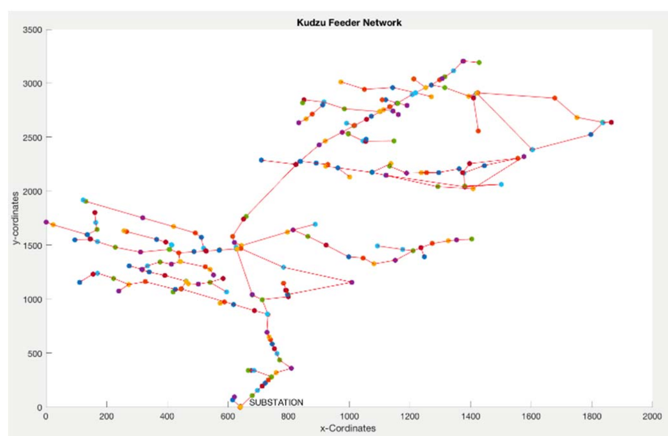


Fig. 1. Case study – Topology of Kudzu feeder


Fig. 2. Extraction of odd and even vertices- Kudzu feeder

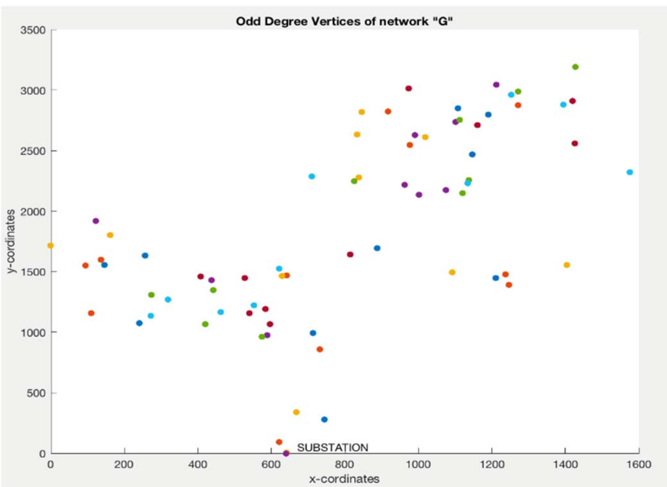


Fig. 3. Odd degree vertices – Kudzu feeder

dot represents a vertex of the network at given coordinates and edges are represented by line connecting between vertices.

In the first phase, odd degree vertices are identified. Fig. 2 shows all vertices of the Kudzu feeder network. Dots which are filled represent odd degree vertices and empty dots represent even degree vertices. The Kudzu feeder has a total of 176 even

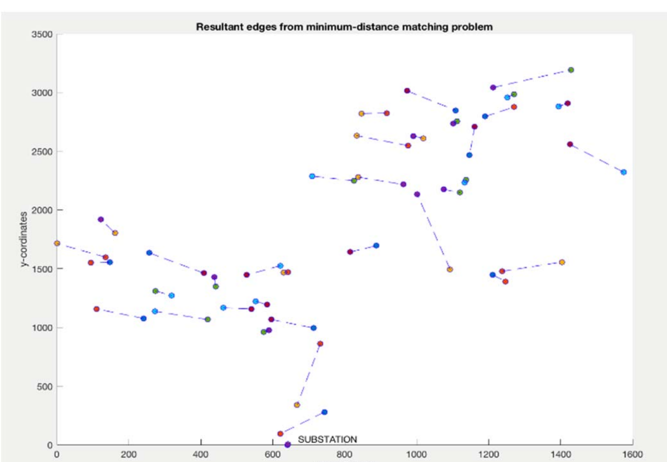


Fig. 4. Odd degree vertices – Kudzu feeder

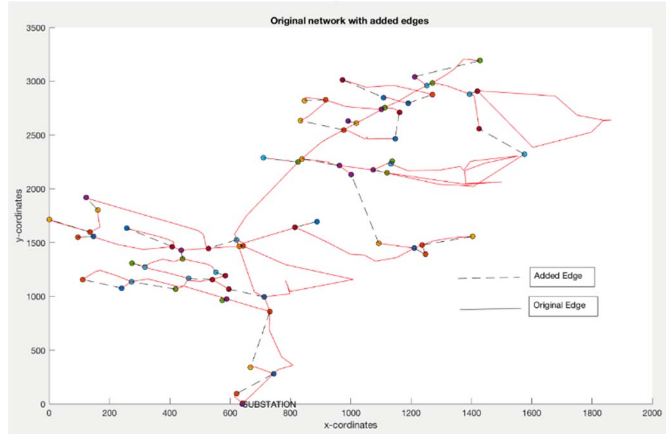


Fig. 5. Augmented network with added edges-Kudzu feeder – Kudzu feeder

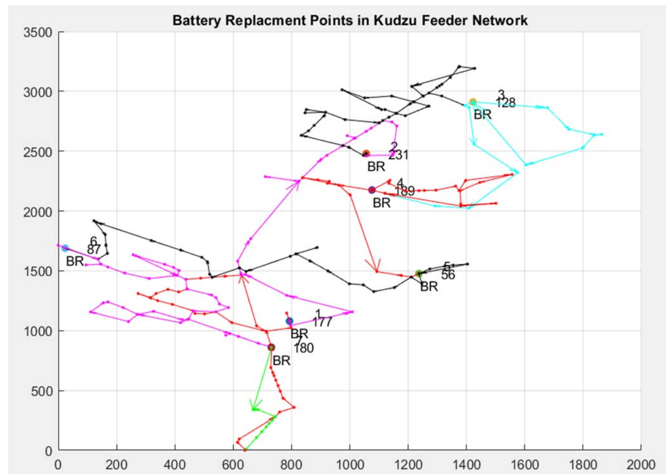


Fig. 6. Segments of drone flights with battery replacement

degree vertices and 72 odd degree vertices. As the result of phase I, an undirected complete network $\overline{G}(\overline{V}, \overline{E})$ is formed, where $\overline{V}$ represents odd degree vertices and $\overline{E}$ represents edges connecting all odd vertices. Fig. 3 shows only odd degree vertices. These edges are added to the original network $G\ (V, E)$ to construct $G'(V, E')$ as in Fig. 5. Phase–III is applied to obtain

TABLE I. RESULTS OF KUDZU FEEDER NETWORK BASED ON VARYING SPEED OF DRONE

| Speed | Time | Number of Segments | Total Inspection Time |
|---|---|---|---|
| 7mph | 1.87 | 8 | 183.27 |
| 9mph | 2.40 | 6 | 158.10 |
| 11mph | 2.93 | 5 | 142.08 |
| 13mph | 3.47 | 4 | 130.99 |
| 15mph | 4.00 | 4 | 122.86 |
| 17mph | 4.53 | 3 | 116.64 |

a drone path. A binary integer programming problem is solved to find a minimum distance matching for $\overline{G}$. Fig. 4 is the result of the minimum distance matching (Phase II), where 36 additional edges are obtained.

For the case study, a specific commercial drone model, called DJI Phantom 3 Pro [15], is considered to characterize the drone specification. DJI Phantom 3 Pro has a maximum flight time of 23 minutes, which means the battery of the drone has to be replaced well before 23 minutes of flight time. It is assumed that the flight time must not exceed the 16 minutes before replacing the battery. Since the maximum flight time of the drone can be affected by temperature, wind speed, flying style, etc. during the flight, users of DJI Phantom recommend 16 minutes flight time instead of the nominal maximum flight time of 23 minutes [16]. Besides, the average speed of the drone is assumed to be 7 miles/hour which gave good visual inspection to a point of interest in a location based on various flight testing. When other types of drones with different characteristics are used, speed and flight time can be adjusted accordingly, and this will result in change in damage assessment time, total travel time, and battery replacement locations.

Based on these assumptions, it is calculated that a drone can travel a total distance of 1.8 miles when fully charged. Since the drone can travel the maximum of 1.8 miles, the flight path is divided into multiple smaller circuits, each of which can be assessed by a single flight of the drone. The Kudzu feeder has a drone flight path that amounts the total distance of 13.215 mile (69,775 ft.). In this situation, the drone cannot inspect the complete Kudzu feeder network and battery has to be replaced at some points of the path. As the result of the battery replacement procedure vertices 177, 231, 128, 189, 56, 87, 180 are identified as battery replacement points. Therefore, there are eight flight segments. These eight segments are shown in Fig. 6. TABLE I presents the sensitivity analysis of varying speed of the drone.

## V. CONCLUSION

High impact low frequency (HILF) events have created severe disruptions in power distribution systems. In this paper, we consider a damage assessment process in an effort to minimize the restoration time. Exploiting agility and accessibility of drone technology, we propose a three-phase algorithm that provides an efficient drone flight path. This study provides a systematic procedure for damage assessment utilizing agile drone technology along with an efficient flight path for the drone.


## ACKNOWLEDGMENT

This study was partially supported by Supplement of SRNS A15-0251.


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