Multimodal Prescriptive Analytics for Rapid Post-Disaster Inspection Operations

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1 INTRODUCTION

Critical infrastructure networks, such as electricity, water, oil and gas distribution networks, regularly face risks of service disruptions due to component failures caused by disaster events (e.g., hurricanes, earthquakes). These failures often result in significant societal and economic losses: The 2017 hurricane season resulted in a record $306.2 billion in damages (NOAA, 2022). Following a disaster event, the primary role of a utility company is to inspect its network to promptly identify failures and subsequently restore its service. However, inspection operations are hindered by the uncertainty pertaining to the failures' locations, resulting in an increase in response time and cost. Thus, a significant amount of stochastic routing models have been developed in the literature for response operations (de la Torre *et al.*, 2012). In addition, researchers have leveraged new data analytics to improve post-disaster failure predictions and reduce diagnostic uncertainty (Nateghi *et al.*, 2011). Finally, unmanned aerial sensors (UASs) provide new technological opportunities to improve network inspections for post-disaster assessment (Ezequiel *et al.*, 2014). Our goal is to leverage these three research areas to develop a *multimodal analytics approach for post-disaster network inspection.*

In this work, we formulate a prescriptive analytics model for network inspection operations. We first develop a predictive model that provides spatial estimates and uncertainty bounds on the number of failures throughout an infrastructure network after a disaster event. Then, we leverage these predictions to prioritize network inspection involving UAS-equipped ground crews. After each day of inspection, we integrate the information from partially inspected regions to schedule inspections in subsequent days. To solve this large-scale problem, we propose a solution approach based on a certainty equivalent mixed-integer program (MIP) that (i) decomposes the inspection of UASs over subnetworks and the routing of inspection crews between access points from where UASs can be launched; and (ii) integrates failure information from current inspections to refine the uncertainty bounds on the remaining number of failures. We evaluate our solution approach on Houston's drainage network using debris data identified after Hurricane Harvey in 2017.

2 PROBLEM DESCRIPTION

We consider a utility company that seeks to dispatch inspection crews equipped with UASs to identify failures within a critical infrastructure network caused by a natural disaster. After the natural disaster occurs, the utility has access to local information on the critical network (from owned sensors or crowdsourced data). We use this information to partition the network into

N directed subnetworks $\mathcal{G}_n := (\mathcal{V}_n, \mathcal{E}_n)$ and predict – with a Machine Learning algorithm – the number of failures within each subnetwork. For every $n \in [N]$, we let D_n^1 denote the random variable representing the number of failures in subnetwork $\mathcal{G}_n$.

To identify the failures' locations and/or reduce the uncertainty regarding the number of failures in each subnetwork, m inspection crews, each equipped with U UASs, originate at a service station s and travel in vehicles along the road network to reach access points a_n from where they operate the UASs to (partially) explore the corresponding subnetworks $\mathcal{G}_n$. Each inspection crew then retrieves their UASs and travels by vehicle to another subnetwork's access point for another inspection. They repeat this process until the end of their shift, which lasts H time units, and then return to the service station. At the end of each day, we gather the newly acquired data and update the estimate of the number of failures that remain in each subnetwork.

Let $\mathcal{A} := \{a_n,\ n \in [N]\}$, with $[N] := \{1, \dots, N\}$, denote the set of access points. For every ordered pair of locations $(i, j) \in (\mathcal{A} \cup \{s\})^2$, we denote μ_{ij} the vehicle travel time between i and j. For every subnetwork $n \in [N]$ and every edge $(i, j) \in \mathcal{E}_n$, we denote its length by ℓ_{ij}. When flying over an edge of a subnetwork, a UAS can either travel at a nominal speed $1/\nu^-$ that enables the identification of failures along that edge, or it can travel at a faster speed $1/\nu^+$, which reduces the travel time but does not permit the identification of failures along that edge. This feature is useful to permit the coordination of multiple UASs and avoid redundancy of effort.

We can then model the set of feasible dispatches using mixed-integer linear constraints. For every ordered pair of locations $(i, j) \in (\mathcal{A} \cup \{s\})^2$ with $i \neq j$, we denote x_{ij} the binary variable equal to 1 if an inspection crew travels from i to j, and we denote $v_{ij} \in \mathbb{R}_{\geq 0}$ the variable representing the time at which the inspection crew traveling along (i, j) arrives at location j. Next, for every subnetwork $n \in [N]$, every directed edge $(i, j) \in \mathcal{E}_n$, and every UAS $u \in [U]$, we consider the binary variable y_{ij}^u (resp. z_{ij}^u) equal to 1 if UAS u travels from i to j at nominal speed (resp. faster speed). We also consider the nonnegative variable w_{ij}^u representing the time (since takeoff at a_n) it takes for UAS u to arrive at location j. Since the inspection crew needs to retrieve all dispatched UASs before traveling to the next subnetwork (or back to the service station), we consider for each subnetwork $n \in [N]$ a variable r_{a_n} representing the time spent at that subnetwork, characterized by the longest flight time of the U UASs. We can now formulate the mixed-integer linear constraints to model the feasible crew dispatches and UAS flight plans:

$$\sum_{j \in \mathcal{A}} x_{sj} \leq m, \tag{1}$$

$$\sum_{j \in \mathcal{A} \cup \{s\}} x_{ij} = \sum_{j \in \mathcal{A} \cup \{s\}} x_{ji}, \qquad \forall\, i \in \mathcal{A} \tag{2}$$

$$\sum_{j \in \mathcal{A} \cup \{s\}} x_{ij} \leq 1, \qquad \forall\, i \in \mathcal{A} \tag{3}$$

$$\sum_{i \in \mathcal{V}_n} (y_{a_n i}^u + z_{a_n i}^u) \leq \sum_{j \in \mathcal{A} \cup \{s\}} x_{a_n j}, \qquad \forall\, n \in [N],\ \forall\, u \in [U] \tag{4}$$

$$\sum_{j \in \mathcal{V}_n} (y_{ij}^u + z_{ij}^u) = \sum_{j \in \mathcal{V}_n} (y_{ji}^u + z_{ji}^u), \qquad \forall\, n \in [N],\ \forall\, u \in [U], \forall\, i \in \mathcal{V}_n \setminus \{a_n\} \tag{5}$$

$$y_{ij}^u + z_{ij}^u \leq 1, \qquad \forall\, n \in [N],\ \forall\, u \in [U],\ \forall\, (i, j) \in \mathcal{E}_n \tag{6}$$

$$\sum_{u=1}^{U} y_{ij}^u \leq 1, \qquad \forall\, n \in [N],\ \forall\, (i, j) \in \mathcal{E}_n \tag{7}$$

$$0 \leq w_{ij}^u \leq M(y_{ij}^u + z_{ij}^u), \qquad \forall\, n \in [N],\ \forall\, u \in [U],\ \forall\, (i, j) \in \mathcal{E}_n \tag{8}$$

$$w_{a_n j}^u = \nu^- \ell_{a_n j} y_{a_n j}^u + \nu^+ \ell_{a_n j} z_{a_n j}^u, \qquad \forall\, n \in [N],\ \forall\, u \in [U], \forall\, j \in \mathcal{V}_n \tag{9}$$

$$\sum_{j\in\mathcal{V}_n} w_{ij}^u = \sum_{j\in\mathcal{V}_n} w_{ji}^u + \sum_{j\in\mathcal{V}_n} (\nu^- \ell_{ij} y_{ij}^u + \nu^+ \ell_{ij} z_{ij}^u), \quad \forall\, n\in[N],\ \forall\, u\in[U], \forall\, i\in\mathcal{V}_n\setminus\{a_n\} \tag{10}$$

$$r_{a_n} \geq \sum_{i\in\mathcal{V}_n} w_{ia_n}^u, \quad \forall\, n\in[N],\ \forall\, u\in[U] \tag{11}$$

$$v_{sj} = \mu_{sj} x_{sj}, \quad \forall\, j\in\mathcal{A} \tag{12}$$

$$0 \leq v_{ij} \leq H x_{ij}, \quad \forall\,(i,j)\in\mathcal{A}^2 \tag{13}$$

$$\sum_{j\in\mathcal{A}\cup\{s\}} v_{ij} = \sum_{j\in\mathcal{A}\cup\{s\}} v_{ji} + r_i + \sum_{j\in\mathcal{A}\cup\{s\}} \mu_{ij} x_{ij}, \quad \forall\, i\in\mathcal{A}. \tag{14}$$

Constraints (1)-(3) model the tours taken by the m inspection crews. Constraints (4) permit the exploration of a subnetwork by UASs only if a crew reaches its access point. Constraints (5) ensure conservation of the flow of UASs within $\mathcal{G}_n$. Constraints (6) ensure that one speed is selected (nominal or faster) for each edge traversed by a UAS. Constraints (7) ensure that each edge is inspected for failure identification by at most one UAS. Constraints (8)-(10) monitor the flying time of each UAS and eliminate subtours. Constraints (11) determine the time spent by an inspection crew at each subnetwork. Finally, the remaining constraints (12)-(14) determine the total working time of each inspection crew and eliminate subtours.

Let $\mathcal{X}$ denote the set of feasible solutions to the set of constraints (1)-(14). Let T denote an upper bound on the number of days required to explore all subnetworks. Then, each day $t\in[T]$, we select a feasible dispatch and flight plan $X^t\in\mathcal{X}$. After each day of inspection, we process the data gathered by UASs and update our estimate of the number of failures in the subnetworks that have been partially explored. The distribution of the number of failures within each subnetwork is updated using Bayes' rule. In deriving the computations, we assume that the failures are uniformly spread throughout each subnetwork. Thus, conditional on the total number of failures $d_n^t \sim D_n^t$ within a subnetwork and the fraction γ_n^t of the subnetwork that is explored on day t, the number of failures identified by the UASs f_n^t follows a binomial distribution $F_n^t = B(d_n^t, \gamma_n^t)$.

Every day $t\in[T]$, the state of the system is characterized by $\boldsymbol{\mathcal{R}}^t = (\mathcal{R}_1^t,\ldots,\mathcal{R}_N^t)$ and $\boldsymbol{D}^t = (D_1^t,\ldots,D_N^t)$, which respectively represent the set of unexplored edges and the distribution of the number of remaining failures in each subnetwork at the beginning of day t. The objective is to maximize the number of failures identified each day. Then, the decision problem can be formulated using the following multi-stage stochastic optimization problem:

$$\forall\, t\in[T], \quad q^{t^*}(\boldsymbol{\mathcal{R}}^t, D^t) = \max_{X^t\in\mathcal{X}} \mathbb{E}_{\boldsymbol{D}^t}\Big[\mathbb{E}_{\boldsymbol{F}^t}\Big[\sum_{n=1}^{N} f_n^t + \delta q^{t+1^*}(\boldsymbol{\mathcal{R}}^{t+1}, \boldsymbol{D}^{t+1})\Big]\Big] \tag{15}$$

$$\text{with } \gamma_n^t = \frac{1}{\sum_{(i,j)\in\mathcal{R}_n^t} \ell_{ij}} \sum_{u=1}^{U} \sum_{(i,j)\in\mathcal{R}_n^t} \ell_{ij} y_{ij}^{ut}, \quad \forall\, n\in[N] \tag{16}$$

$$F_n^t = B(d_n^t, \gamma_n^t), \quad \forall\, n\in[N] \tag{17}$$

$$\mathcal{R}_n^{t+1} = \mathcal{R}_n^t \setminus \{(i,j)\in\mathcal{E}_n \mid \sum_{u=1}^{U} y_{ij}^{ut} \geq 1\}, \quad \forall\, n\in[N] \tag{18}$$

$$D_n^{t+1} = \pi^t(D_n^t, \mathcal{R}_n^t, X^t, f_n^t), \quad \forall\, n\in[N], \tag{19}$$

where $\delta\in(0,1)$ is a discount factor to model the importance of identifying failures as early as possible. Equations (16) determine the fraction of previously unexplored edges in each subnetwork that are inspected on day t, which in turn impact the distributions of the numbers of identified failures given in equations (17). Equations (18) update the sets of unexplored edges in each subnetwork for the following day, and equations (19) update the distribution of the number of failures remaining in each subnetwork using Bayes' rule.

3 CURRENT RESULTS

To solve the multi-stage stochastic routing problem (15)-(19), we propose a certainty equivalent MIP that is solved on a rolling horizon. To scale this approach, we replace the set of constraints (4)-(11) by the selection of likely UAS flight plan options that are precomputed by solving a MIP that generalizes the minmax k-Chinese postman problem (Frederickson *et al.*, 1978). We evaluate our solution approach using the data from the inspection operations in Houston, TX, after Hurricane Harvey in 2017. Specifically, the flood control district was tasked with finding debris along its drainage network that led to important and costly floods throughout the city. To estimate the distribution of the number of failures on the first day after the hurricane, we trained a multivariate Poisson regression model using environmental data and readings from a network of fixed gauge sensors. Figure 1 shows the location of the debris on the drainage network, as well as the performance of our solution approach in comparison with a greedy heuristic – with simpler data analytics and no UAS capabilities – designed to represent the 2017 inspection operations.

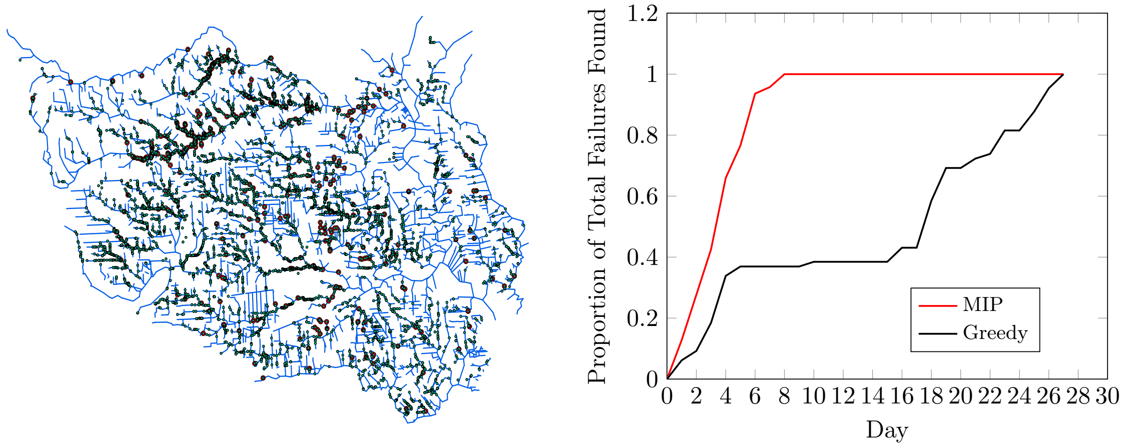

Figure 1 – *Houston's drainage network with failures (left) and evaluation of our solution (right).*

From Figure 1, we observe a significant improvement in the inspection operations compared to the greedy heuristic. This improvement is due to (i) the added speed provided by UASs, (ii) the smarter coordination of resources from the MIP, and (iii) the reduced diagnostic uncertainty, obtained from the initial regression model and the daily Bayesian updates using the information from partially inspected subnetworks. Next, we aim to improve our solution approach with more complex decomposition methods for dynamically computing near-optimal UAS flight plans and by directly accounting for the failure uncertainty bounds in the certainty equivalent MIP.

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