Location of disaster assessment UAVs using historical tornado data

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ABSTRACT
Preparing and responding to disasters is a complicated task. One must balance coverage of SAR resources versus preparation cost. This article presents a method and solution to prepositioning UAV damage assessment and search teams in Oklahoma using historical tornado data. The approach is based on set covering and multi-station vehicle routing models. It also presents a method to robustify the solution in the event a UAV team cannot be activated to respond to the disaster. This can simulate a team unable to respond. Results show 70% more stations and teams being required when chance of a depot failure goes from 0 to 5% and 90% more stations required when 0–10%. We find that when trying to use a solution that does not account for depot failure, the system of UAVs cannot meet search completion targets in 3–4% of cases. These results demonstrate accounting for the chance of teams not being able to respond to domestic disasters is important and failing to do so means an increased chance of not being able to respond adequately to disasters and incorporating the chance of station failure has a profound impact on the number of stations needed.

Introduction
Preparing for disasters and the subsequent Search and Rescue (SAR) operations involves a variety of decision problems that can be addressed with operations research methodologies (Green and Kolesar 2004; Simpson and Hancock 2009). SAR operations present a variety of decision-making problems at the strategic, tactical, and operational levels. These problems include determining the number and type of resources used in an SAR operation (e.g., helicopters, fixed wing aircraft, Emergency Medical Technicians and other first responders), locations for these teams and tools, and identifying search teams’ needs and capabilities. The strategic aspect of SAR operations concerns the determination of the locations of guard and search team stations and resources depots or launch points. The strategic level also includes long-run
planning problems, such as enhancing the capabilities of the SAR fleet in terms of flight crew number or increasing the number of stations that can be activated. All these decisions are often done in advance of a disaster occurring.

One aspect of the emergency response systems, e.g., SAR operations, includes resource allocation. Resource deployment decisions are often made in conjunction with computer-assisted modeling of the probability of detection under various deployment scenarios (Afshartous et al. 2009). This can be compared to and contrasted with operational decisions are guided via established survival tables to guide the SAR routing efforts and advanced technology designed to maximize the probability of detecting a point of interest.

Procedures at the strategic, tactical, and operational level have been developed. The traditional approach has been to deal separately and sequentially with each problem or planning level. Once the station locations are chosen at the strategic level, the actual allocation of resources to each station can be determined, and the airborne vehicle routes are determined last.

In recent years, many developments in SAR airborne technologies have increased to improve operations and reduce the time span to assess and search a damaged area in real-time. These technologies include airplanes and helicopters equipped with numerous sensors as well as Unmanned Aerial Vehicles (UAVs), also called drones, equipped with cameras and wireless sniffers to detect the presence and roughly the proximity to a cellular device. The reasoning is that knowing where people are in the event of a disaster with structural destruction means rescue teams can triage where to initially focus their efforts. The support provided by UAVs, as well as the use of wireless sniffer sensors, can allow rescuers to better prioritize areas to conduct SAR operations.

The problem studied in this article is an application of the location and routing problem. We are trying to solve strategic questions in the SAR operation. Here we determine the choice and location of stations that search teams will be allocated to before a tornado disaster. We develop a metaheuristic to choose what stations are selected to get a permanent UAV search team. We use metaheuristics as the location-routing problem is NP-hard (Fitzsimmons 1971; Gendreau et al. 1997). We then test the solution on various artificial scenarios to determine the effectiveness of the selected stations when considering different failure criteria. We leverage the past work of (Grogan et al. 2021) to conduct the routing algorithms of this problem.

We also aim to answer the question what if there is a situation where UAV is unable to launch to respond to a tornado. Such scenarios could be the station itself was struck by the tornado and the crew is unable to launch the UAV due to damage, the UAV was undergoing routine maintenance off site and does not exist at the station, or crew members themselves are victims of the tornado striking (such as they are trapped at home or en route to a station to operate the UAV). We therefore aim to robustify the solution against this uncertainty. Robust optimization is often juxtaposed to stochastic optimization where the latter attempts to optimize an expected value, where the former attempts to identify solutions that are likely to still give quality solutions.

The remainder of the article is as follows. Section 2 presents a brief literature review on UAV routing for SAR operations. Then, Section 3 provides a definition of
the problem and its context. Section 4 outlines the data used and methods for solving the problem, while Section 5 outlines the testing procedure. Section 5 discusses the results before concluding the article in Section 6 with a general discussion and identifying future research perspectives. Appendix A contains pseudocode of algorithms outlined in this article. Appendix B formally defines models mathematically from this article. Appendix C references where data can be accessed that was used in this article. Appendix D outlines notation and acronyms that appear in this article.

**Literature review**

A detailed breakdown of the use of UAVs in disaster response and SAR operations can be found in Beck (2016) and Grogan et al. (2018). The use of UAVs for SAR operations also appears in wilderness search and rescue (Kashino et al. 2019), earthquake response (Beck 2016; Beck et al. 2016, 2018; Dominici et al. 2017; Golabi et al. 2017), mountain rescue operations (Silvagni et al. 2017) and hurricane response (Fernandes et al. 2019; Murphy et al. 2008). The only work so far that incorporates UAVs in response to tornadoes is in Grogan et al. (2021).

Giordan et al. (2017) also discussed the use of UAVs in monitoring application and management of natural hazards. Within that literature, routing problems and facility location problems form an important aspect of SAR operations planning. Routing problems for SAR operations consist of determining a set of routes, each performed by a drone that starts and ends at its own depot (launch point), such that all points of interest of the affected area are visited, all the operational constraints are satisfied, and the length of time for the longest search route of a drone is minimized. UAVs have a hard endurance constraint (fuel tank, battery life) and will crash if the UAV does not safely land close to its launch point. Furthermore, each UAV requires a two-to-three-person team to setup, launch, and operate the UAV.

The literature in UAV routing for SAR operations highlights the use of the close enough vehicle routing problem formulation in routing UAVs, since the UAV does not need to visit each potential victim location directly but rather must get close enough (within detection range) to a potential victim. In addition, the feasibility of the UAV equipped with the wireless sensor for mapping victim location has been demonstrated in the literature (Beck 2016; Beck et al. 2016, 2018; Liu et al. 2014; Mirowski et al. 2013; Sardouk et al. 2010).

Station location and resource allocation problems concern the strategic and tactical aspects of SAR operations. These problems have been broadly studied from two perspectives: deterministic and stochastic. Deterministic models include covering, center, and median models. Covering problems are very common in the emergency services field (Fitzsimmons 1971; Gendreau et al. 1997). Stochastic models deal with the allocation of resources in a stochastic environment, e.g., in cases where customer demands, distances, or costs are random (Karatas et al. 2017). Stochastic models also consider multiple future scenarios with respect to customer demand (Daskin and Hesse 1997) and treat the travel distance as uncertain, e.g., depending upon the time of day for the ambulance location problem.
We are unable to find any location and allocation research conducted at the intersection of tornado preparations, UAV usage, and locating the UAV tool in preparation of tornados occurring. In addition, very little work has been published concerning station location, resource allocation, and routing problems for SAR operations. In our case, we draw upon and adapt the research that use the context of maritime security forces to prepare for distress calls from ocean vessels. For example, (Abi-Zeid and Frost 2005; Afshartous et al. 2009; Karatas et al. 2017) try to optimize the distribution of Maritime SAR helicopters along the coasts of Canada, the United States, and Turkey, respectively. These three papers use simulations based on past distress calls to allocate the helicopters. In these papers, when a distress call is received, SAR helicopters are dispatched directly to a distress call. (Abi-Zeid and Frost 2005) presented a decision support system for SAR operations. The system allows to determine the dimension and location of the search area and the search sub-areas and the assignment of the available SAR units to their corresponding sub-areas. Afshartous et al. (2009) proposed a simulation and optimization-based approach that enables the determination of robust locations for coast guard stations in the presence of uncertainty in distress call locations, i.e., such that the stations are adequately located with respect to distress calls that vary over time. First, distress call locations are simulated based on a real data set of distress calls. These patterns then serve as input to a p-uncapacitated facility location problem to determine p locations for responding stations. The approach also provides guidance to the tactical question of how the resources (e.g., helicopters, fixed wing aircrafts) should be allocated across stations. Karatas et al. (2017) formulated a p-median model for allocating helicopter resources to candidate stations with the objective of minimizing total response time to incidents (distress calls). The model determines the stations to be activated as well as the number and type of helicopters to be deployed at each station (Karatas et al. 2017) also included probability distributions of helicopter failure rates, maintenance period distributions—a helicopter is inoperable during maintenance time—and inclement weather suspending operations. Still, at the strategic and tactical levels, Jurecka and Niedzielski (2017) proposed a methodology for delineating priority sectors of spatial coverage for the UAV in order to support SAR operations. Sectors with high probability of containing the signal of a missing person are defined to optimally allocate resources, and consequently shorten the field search.

While these works offer a great starting point for this article, there is a lack of literature in the use of active and granular meteorological data (such as tornado watches and warnings) in locating UAV depots. In addition these papers lack the necessity of conducting a ‘search’, all the helicopters are dispatched directly to the distress call rather than having to identify the location of a distress call.

There has been research in incorporating uncertainty in weather conditions into routing UAVs (Cheng et al. 2020), although a look is strictly given at wind conditions. Wright (2018) studied a severe weather event that includes tornados; however, the method they use to update the travel times between cities revolves around perception (rain, snow, fog, etc.) causing delays in transportation, not assessing the damage caused by tornados. In addition, most resource allocation models involving ‘server-to-customer’ type operations, such as firefighting, emergency incident response, first
aid (ambulance services), and SAR at sea, do not account for the effects of unexpected equipment breakdown and weather condition issues to the performance of the optimal solution. In most real-life situations, the performance is affected due to unexpected delays or unavailability of scarce resources.

Recently, Grogan et al. (2021) proposed using a combination of UAVs and meteorological data from the National Weather Service (NWS) to identify the location of a potential assessment area after a tornado occurs. Powerful tornados are frequent in large parts of the central United States. A tornado is a rotating column of air that can cause severe destruction to property and loss of life when the rotating column is in contact with the ground. It is difficult to track this path of destruction remotely, as well it is impossible to know the scale of the tornado until after surveying the destruction. A search area is selected from a combination of data from the NWS called a storm-based warning (SBW) and a local storm report (LSR). The SBW is a polygon where potential severe weather might occur, and the LSR is the occurrence of a severe weather event. The search area is further delineated by the assumption that most people in need of aid will be in close proximity to a named road (i.e., a road in the official road network of a state). This combination of a delineated search area, a road network to further limit the search area, and a UAV that can identify where people might be in need is used in unison to deploy UAVs in the aftermath of a tornado.

**Problem description and context**

The problem can be defined as follows. Given the use of UAVs for assessing damage and identifying areas to deploy SAR teams in the aftermath of a tornado, where should state officials preposition these teams in such a way to minimize the number of UAVs deployed/prepositioned while ensuring a maximum amount of time to assess an area. The UAV in question was defined in Beck et al. (2016). The UAV is a fixed-wing gas-powered aircraft, a wingspan of 3.3 m, a top speed of 22 m/s, and an endurance of 8 h.

In addition, given the probability of a UAV not being able to launch, how do we account for and plan for this happenstance.

In this context, fire stations can be used as depots to locate UAV teams. To solve this problem, we propose a stochastic scenario-based model that considers multiple historical tornado scenarios and treat the UAVs locations as uncertain, e.g., depending on if one or more UAVs is not able to provide services in the case of equipment breakdowns. We seek the determination of robust locations for stations, i.e., locations that are robust over the tornado scenarios in the presence of equipment breakdowns.

Therefore, to identify the location of a potential assessment area after a tornado occurs, Grogan et al. (2021) proposes using a combination of a UAV tool and meteorological data from the NWS. The UAV tool used was proposed in Beck (2016) and is a fixed-wing, unmanned, and remotely controlled aircraft equipped with cameras and a wireless sniffer. The wireless sniffer is a generic term for a device to detect the presence of, direction to, and distance to a cellular device. In combination with observing a damaged or destroyed structure, using a wireless sniffer means first
responders can estimate where and how many people require aid in the event of a disaster. A search area is selected from a combination of data from the NWS called a SBW and an LSR. The SBW is a polygon where potential severe weather might occur and the LSR is the occurrence of a severe weather event (specifically a tornado occurring). The search area is further delineated by the assumption that most people in need of aid will be in close proximity to a named road (i.e., a road in the official road network of a state). This combination of a delineated search area, a road network to further limit the search area, and a UAV that can identify where people might be in need is used in unison to create a search tool to aid first responders in identifying people in need of aid.

To solve the problem, we interpret the goal as a location problem and use techniques for the location and routing problem and/or a multi-depot vehicle routing problem where it is not required to use every depot. A full breakdown of the notation used in this document can be found in Table 1. From the collection of depots $D$, we assign at most one UAV team to a depot. While UAVs have become easier to use, there is still no fully autonomous solution and still require operators to maintain, launch, operate, and retrieve the UAVs. Because of these hands-on requirements of operating UAVs, there is a chance that a UAV may not be able to launch. This could be because operators may not be able to make it to a fire station because they are victims themselves, or a fire station could be damaged because of the storm. We define this chance as a probability of a station being “down” as $p_{\text{down}}$. To solve the location problem, we use the collection of historical tornado events $e \in \mathcal{TE}$ to define the routes and/or service area of each historical scenario. Let $\bar{T}_{\text{target}}$ be a service time upper bound within which we want to complete a search.

Our focus is on the state of Oklahoma. There are 1185 fire stations listed in the state of Oklahoma, and previous work has noted that any and all of the fire stations in the state can be used as a depot (Grogan et al. 2021). It is financially unlikely to fund a UAV team for each depot. The next section describes our data preparation process and solving approach.

Table 1. Notation.

| Notation | Meaning |
|----------|---------|
| $D$      | Collection of candidate depots |
| $p_{\text{down}}$ | The probability (percentage) chance that any given station $s \in S$ will not be able to launch |
| $r_{\text{scan}}$ | The parameter defined as the scanning radius (range) of the UAV. In this article, $r_{\text{scan}}$ is 300 meters |
| $\mathcal{TE}$ | Collection of historical tornado events |
| $e$ | Lowercase $e$, a specific scenario in a collection of scenarios $\mathcal{TE}$ |
| $T_i, i \in D$ | Defined as the time (cost) it takes a specific route $i$ to complete its route |
| $T$ | In the context of a vehicle routing problem, $T$ (Tee Bar) represents the time (or any cost metric) of the route with the maximum distance (or cost). In mathematical notation: $\bar{T} = \max\{T_i\} \forall i \in D$. $T$ can be similarly interpreted to the makespan of a project. In the context of this article, this is the time it takes the UAV (of all UAVs launched) with the longest time to complete its route |
| $\bar{T}_{\text{target}}$ | Defined as the maximum value $T$ can take and a solution be feasible. |
| $S_k$ | The solution (collection of depots) that are selected for testing. The subscript $k$ represents the iteration of the metaheuristic |
| $S_{p_{\text{down}}, F_{\text{target}}}$ | The final solution from our metaheuristic with the parameters $p_{\text{down}}$ and $F_{\text{target}}$ |
| $N_{\text{feas}}$ | A counter that keeps track of the number of historical tornado events $\mathcal{TE}$ that are covered by the solution $S_k$ |
| $F_{\text{target}}$ | A minimum percentage of historical tornado events $\mathcal{TE}$ that are adequately covered by the solution $S_k$ |
Data and methods

To generate the selection of fire stations for this article, we decompose the problem into three parts: Section 4.1 where we discuss the Generation of waypoints; Section 4.2 where we generate an initial solution with a Selection of Depots Heuristic; finally, Section 4.3 where we present how to solve the Station-Location Problem. After we have solution(s) generated from the method outlined in Section 4.3, we test the quality of the solution against artificial cases generated from real-world data. This procedure is outlined in Section 4.4.

Generation of waypoints

Points of interest are indications of where people might be in the event of a natural disaster. These points are generally aggregated into sectors called waypoints. In this article, waypoints are created based on the geospatial road data that exists within the bounds of the search area (bounds created by the weather data). Waypoints can be thought of as the center of a disk that contains a number of points of interest. The demand for each point of interest can be considered to be equal, although this could be changed to model situations where different distress calls receive more weight (or a priority) according to population density or the severity of the damage observed.

To generate the waypoints for each disaster, we use the work by Grogan et al. (2021). We assume that people in need of aid will be on or near the public road network in the case of a tornado disaster. We decompose the road network into “points of interest.” This decomposition occurs by converting the “polyline” geospatial data that represents the road network in the state of Oklahoma into discrete points. A polyline here is a spatial geometry that is created by a sequence of coordinates that typically make up the centerline of a road. We use these centerline points as “points of interest” and if any pair of points on the polyline is greater than the scanning radius $r_{scan}$ of our device, we place additional points on the line between the two points such that no two points are more than the scanning radius $r_{scan}$ apart. All these points are used as “points of interest” for creating the waypoints. The creation of waypoints is an extension of the set covering problem. Due to the set covering being NP-Hard and the number of sets being very large, we use the Steiner Zone Heuristic developed in Grogan et al. (2021). The Steiner Zone Heuristic selects a point of interest at random (i.e., a portion of the road network in this case) and creates a temporary group. From the selected group, the algorithm will continually add points of interest from the road network that are within $r_{scan}$ of all other points of interest in the temporary group. Once there are no further points to add, the center of the smallest enclosing circle is then used as a “waypoint.” After this has been completed, all the points from in the temporary group are removed from the initial collection of points of interest. The heuristic then selects a new initial point of interest, and the process repeats until all points of interest are at most $r_{scan}$ from a waypoint. For our instance, we have set $r_{scan} = 300$ m. For a detailed description of the Steiner Zone Heuristic see Algorithm 1 in Appendix A.
**Selection of depots heuristic**

The proposed strategy to find the minimum number of depots (fire stations) consists of solving a set covering problem and a vehicle routing problem. We define the mathematical model for this problem in Appendix B.

To generate an initial and a well-balanced set of fire stations, we used a greedy heuristic based on solving a multi-knapsack problem. The multi-knapsack problem is an extension of the knapsack problem where one tries to find the greatest value of items to carry in multiple knapsacks while taking into account the knapsacks’ capacities. In our problem, each knapsack will represent a depot, and we attempt to minimize the number of depots while ensuring all the items (waypoints) can be carried. The capacity of our knapsacks is fixed and homogenous, the value of each item is homogenous, and the weight of the items varies based on the knapsack it is being placed in.

Applied to our case, the weight of the items is the distance from the waypoints to each fire station and the capacity of the knapsack is expressed as a maximum total distance that cannot be exceeded. Practically speaking, all waypoints will have a different weight (distance) depending on which knapsack (fire station) it is assigned to. We solve this problem heuristically by assigning the item (waypoint) with the smallest weight to the knapsack (fire station). We then continue to add items (waypoints) that have the smallest weight (distance) to the knapsack (fire station) until it is full. We then repeat the process by selecting the next item-knapsack (waypoint-fire station) pair with the minimum weight (distance). The pseudocode for this algorithm can be seen in Appendix A, Algorithm 2: Multi-knapsack inspired initial solution.

This heuristic works well for our specific needs. The classical knapsack and multi-knapsack problems have homogenous weights and values, and given binary decision variables, these problems are NP-Hard (Rinnooy Kan et al. 1993). However, since our weights vary depending on the knapsack the item is placed in, there will typically be a ‘best knapsack’ an item can be placed in. Because of this, our greedy heuristic can find a solution rather quickly that matches the number of stations an exact solver solution that has been running for over a day.

**Solving the station-location problem**

To solve the Station-Location Problem, we use the data generated from the previous sections and we propose a ‘station removal heuristic’. We formally define the deterministic version of our model in Appendix B. Our objective is to minimize the number of fire stations that are selected to ensure that UAVs can scan a tornado search area in approximately $T_{\text{target}}$. We see $T_{\text{target}}$ as the upper bound on the amount of time we want the entire area to be searched. We define $T_i$ as the time it takes UAV $i$ to complete its search and $\bar{T}$ is the maximum $T_i$. We want $\bar{T} \leq T_{\text{target}}$. We define a target feasibility rate $F_{\text{target}}$ as a percentage of historical cases that are served in under the $\bar{T}_{\text{target}}$. Finally, we define the $p_{\text{down}}$ as a probability that any given station would not be able to launch their UAVs for any reason, that is the chance a fire station is “down” (such as, but not limited to: the fire station being struck by a tornado,
operational staff not being able to reach the fire station, operational staff required to attend other duties in an emergency.

To find the solution to our interpretation of the station location problem, we propose a ‘station removal heuristic’ which is a neighborhood search heuristic. This heuristic has a tabu list to ensure a diverse search of local neighborhoods. The heuristic starts with an initial solution, which can be the collection of all possible stations; however, in order to reduce the computational search, the initial solution consists of selecting a small subset of stations that are ideally well distributed across the state using the heuristic from Section 3.2 (which generates a solution with about 20% of the full collection of potential stations).

Each current solution (i.e., a selection of stations) is tested using the collection of historical tornado events $TE$. For each historical tornado event $e \in TE$, the heuristic goes through the list of fire stations and generates a random number for each station. If this number is greater than $p_{\text{down}}$, then the station is ‘up’ and can dispatch a UAV. This process creates the set of available stations. The next step consists of evaluating if the available stations can respond to the tornado event under the $T_{\text{target}}$. This procedure is done $N_{\text{Tests}}$ times for each tornado event to ensure robustness against failure. A counter denoted $N_{\text{feas}}$ tracks the number of times a selection of fire stations successfully responds in under $T_{\text{target}}$ (i.e., $N_{\text{feas}}$ increments by 1 if the response is under $T_{\text{target}}$, 0 otherwise). If the number of feasible tests is greater than the feasibility target, i.e., $N_{\text{feas}} \geq F_{\text{target}}$, the current solution is accepted as a feasible solution. If the number of stations is less than the one obtained in the best solution, the solution is accepted as a new best solution.

Next, a perturbation is applied to the current solution. These solution perturbations can be one of three possible perturbations: (1) removing a station from the solution, (2) swapping a station in the solution with a station outside the solution, and (3) adding a station to the solution. The “station removal heuristic” gets its name from the “removing station” neighborhood, which is further subdivided into three sub-neighborhoods: (1.1) random removal where each station has a random chance of being removed; (1.2) least often removal where the heuristic first calculates for each fire station the frequency at which it is used for all tornadoes and the selection of the station to be removed is carried out randomly, but the chance of being selected is weighed on their frequency; (1.3) most often removed is similar to the least often removed, but with an increased likelihood given to stations selected more often in a solution. These neighborhoods are randomly selected, and their weights are defined by whether the last solution is feasible or not. If the current solution is feasible, we place heavier weights on the ‘station removal neighborhoods’. If the solution $S_k$ (where $k$ is a solution iteration counter) is feasible and also the current best solution, we know that the number of stations in the best solution must be less than the number of stations in $S_k$. If the current solution $S_k$ is infeasible, but $S_{k-1}$ is feasible, one station larger (i.e., $|S_{k-1}| = |S_k| + 1$), and is the same size as the best solution, so if a better solution exists, then it must be the size of $|S_k|$, therefore the “station swapping” neighborhoods is prioritized as that will maintain the same cardinality. Whether the solutions are feasible or infeasible, there is a small chance that a station will be added back to the solution as to increase the diversity of the solutions.
At each step, the solution is stored in a tabu list to avoid coming back to the same solution for a short amount of time (iterations). The heuristic allows infeasible solutions to become the current solution.

In short, the stopping criteria is iterations without improvement for each local iteration and iterations where the solution is infeasible to stop the global iterations. Every time a solution is denoted as infeasible (that is, the value of $\frac{N_{\text{feas}}}{N_{\text{tests}} < F_{\text{target}}}$), the infeasibility counter increases by 1. Once the maximum number of infeasible solutions is reached, the heuristic is reset with the current best solution and starts again. The global reset is repeated a minimum of $\text{MinGlobalIters}$ times. At that point, the global reset is done again if a new best solution is found in the last global iteration. Once a global iteration has completed without a new best solution, the program terminates and returns the current best solution. The heuristic is tuned to solve this strategic problem. That is, there is no intention to use these models in a real-time manner. We developed the stopping criteria is tuned in such a way to allow the meta-heuristic to run longer in an effort to uncover better solutions.

Detailed results (including execution time) can be seen in Table 2 (in seconds) and Table 3 (same data but in hours:minutes:seconds).

**Generation of artificial tornado instances**

To generate the solutions, we use the collection of 124 tornado incidents from 2002-04-18 to 2019-12-28. While this might be sufficient for identifying the fire stations that will be selected, these cases cannot be used to test the solutions. We built an “Artificial Tornado Generator” to create new tornado instances. This generator creates these new cases by taking a current historical tornado incident and randomly placing it somewhere else in the state. Once it is in a new location, we solve the multi-depot-routing problem as previously discussed in Grogan et al. (2021).

**Experiments and results**

To validate the approach, two broad tests are conducted. The first is to assess the sensitivity to the two main parameters: the probability of depot failure $p_{\text{down}}$ and the target feasibility $F_{\text{target}}$. The former could be approximated yet is still largely uncertain;
| Depot failure Rate | 100%   | 99%   | 98%   | 97%   | 96%   | 95%     | 94%     | 93%   | 92%   | 91%   | 90%   |
|-------------------|--------|--------|--------|--------|--------|---------|---------|--------|--------|--------|--------|
| 0%                | 04h10m28s | 04h12m54s | 04h12m51s | 04h07m30s | 04h16m15s | 00h26m45s | 00h33m02s | 00h30m03s | 00h45m17s | 00h32m11s | 00h31m31s |
| 1%                | 11h44m25s | 07h02m16s | 07h58m32s | 06h48m48s | 09h54m48s | 08h54m08s | 09h21m37s | 07h13m34s | 07h10m20s | 08h10m27s | 08h27m38s |
| 2%                | 07h19m03s | 06h17m45s | 07h36m35s | 08h02m11s | 05h31m35s | 08h42m34s | 06h45m07s | 10h32m57s | 07h44m52s | 06h27m56s | 07h50m58s |
| 3%                | 08h33m56s | 08h15m17s | 07h01m07s | 07h05m36s | 06h43m52s | 06h21m48s | 06h35m20s | 08h20m02s | 08h38m30s | 09h20m38s | 09h41m30s |
| 4%                | 13h37m24s | 06h49m39s | 06h21m29s | 07h24m27s | 05h20m08s | 06h30m50s | 08h29m15s | 05h56m04s | 06h46m23s | 06h49m34s | 10h15m43s |
| 5%                | 11h03m07s | 10h04m06s | 07h01m00s | 05h59m20s | 08h08m11s | 10h56m19s | 06h50m21s | 08h58m28s | 08h20m30s | 10h41m05s | 09h01m24s |
| 6%                | 13h57m01s | 07h42m28s | 05h44m08s | 06h23m32s | 06h08m59s | 07h22m53s | 06h35m19s | 07h29m44s | 07h47m26s | 10h31m19s | 08h15m11s |
| 7%                | 14h13m46s | 04h14m42s | 04h10m40s | 06h16m40s | 05h33m08s | 08h43m06s | 05h44m45s | 07h11m45s | 11h16m56s | 08h04m41s | 08h22m04s |
| 8%                | 08h55m30s | 05h07m17s | 07h59m10s | 07h09m45s | 06h17m00s | 08h06m04s | 08h15m35s | 06h41m51s | 08h37m26s | 08h28m34s | 07h28m24s |
| 9%                | 07h33m07s | 04h16m02s | 06h40m29s | 06h27m43s | 07h42m09s | 06h34m26s | 08h54m29s | 09h17m34s | 09h01m43s | 09h10m28s | 09h46m55s |
| 10%               | 10h08m24s | 09h11m25s | 07h15m49s | 06h35m02s | 04h37m40s | 07h31m45s | 07h39m11s | 04h30m00s | 06h40m39s | 07h02m43s | 06h41m01s |
the latter is defined as an objective from decision-makers. The second experiment is to demonstrate the quality of the solutions against unknown cases. We use the method outlined in Section 3.4 to generate unknown tornado events to see if the station positioning matches the target feasibility rate.

**Sensitivity of feasibility versus depot failure**

The sensibility of two parameters denoted as ‘depot failure rate’ and ‘target feasibility rate’ are tested in this section. The depot failure rate is largely unknown and can be largely affected by the structural stability of the depot and staffing policies. The target feasibility rate is a policy decision where the decision-makers can tune the number of operational stations based on the number of historical instances that are adequately served by the solution.

Table 4 shows the results of this sensitivity analysis. First, it validates the efficiency of the heuristic proposed in Section 3.3: the greater the chance of failure, the more stations are required for an adequate response; the higher the feasibility rate, the more stations required to provide an adequate response.

A question that can be raised here is why one would choose a feasibility rate lower than 100%. As can be seen from Table 4 there is a marked reduction in the number of stations from when the feasibility target from 100 to 99%. This can be accounted for the rare times when the size of the search area (number of waypoints) is so numerous that many more depots are required to ensure adequate coverage in the event of a disaster. Considering the number of stations deployed, desiring a targeted feasibility of 100% would require 30% more stations and resources versus a 99% feasibility target. This increases up to an 85% increase in the number of depots when we assume any chance of failure. This sensibility analysis can be useful if the decision-makers decide that responding to the largest tornado outbreaks would be better served by fewer UAVs in the air and having people respond in other ways. As shown in Figure 1, most instances contain less than 10,000 waypoints. A lower feasibility target effectively ignores these larger tornado events.

The following figure, Figure 2, also validates what we expect from a solution to solve where to preposition these UAVs. Regardless of the parameters of the solution we are looking at, we see clusters of stations in the dense metropolitan centers of Oklahoma City.

### Table 4. Sensitivity of depot failure rate versus feasibility rate.

| Deparment Failure Rate | 100% | 99% | 98% | 97% | 96% | 95% | 94% | 93% | 92% | 91% | 90% |
|------------------------|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 0%                     | 101  | 77  | 67  | 41  | 38  | 32  | 30  | 30  | 28  | 28  | 28  |
| 1%                     | 104  | 82  | 65  | 41  | 38  | 35  | 31  | 32  | 29  | 30  | 27  |
| 2%                     | 135  | 85  | 69  | 43  | 41  | 37  | 31  | 32  | 32  | 31  | 29  |
| 3%                     | 141  | 82  | 67  | 44  | 41  | 39  | 35  | 33  | 33  | 32  | 30  |
| 4%                     | 129  | 89  | 72  | 46  | 42  | 39  | 33  | 36  | 33  | 31  | 32  |
| 5%                     | 173  | 88  | 70  | 48  | 41  | 40  | 36  | 35  | 35  | 34  | 32  |
| 6%                     | 166  | 91  | 73  | 48  | 44  | 41  | 39  | 37  | 35  | 34  | 33  |
| 7%                     | 173  | 96  | 75  | 49  | 45  | 42  | 40  | 39  | 34  | 36  | 34  |
| 8%                     | 176  | 99  | 75  | 53  | 48  | 44  | 42  | 38  | 35  | 37  | 35  |
| 9%                     | 177  | 98  | 80  | 53  | 46  | 44  | 40  | 40  | 38  | 36  | 36  |
| 10%                    | 194  | 104 | 80  | 55  | 50  | 46  | 43  | 40  | 40  | 38  | 37  |
Figure 1. Histogram of number of waypoints versus number of occurrences.

Figure 2. Visualization samples of solutions for station locations within the state.
in the center of the state and Tulsa in the northeast. When there is no chance of failure, we see an even distribution of stations. As the failure increases, we begin to see clusters of stations form in parts of the state, such as the western panhandle and around the metro Tulsa and Oklahoma City area. Conversely, as we lower the feasibility targets: the number of stations in the sparsely developed eastern portion of the state is also reduced.

Note the roads in blue in Figure 2 do not represent the totality of the road data used to create the waypoints. The roads displayed are the highways and interstate motorways in Oklahoma. They are displayed to help orient the reader.

**Testing the solution on the artificial tornados**

The second test demonstrates the need to account for the failure rate in the solution method. We denote the solutions as $S_{p_{down}, F_{target}}$, which should be read as the solution in Table 4 with the failure rate of $p_{down}$ and the feasibility rate of $F_{target}$. For simplicity, we take the number as an integer. To ensure the reliability of the solutions, we take the solutions $S_{0,100}$, $S_{5,100}$, $S_{10,100}$, $S_{0,99}$, $S_{5,99}$, $S_{10,99}$, $S_{0,98}$, $S_{5,98}$, $S_{10,98}$ and place them up against 250 randomly generated tornado cases. When solving the tornado case, we apply the failure rate indicated by the solution. For example, $S_{0,100}$ gets a 0% failure rate, $S_{5,98}$ is 5%, and so forth.

We also demonstrate the need to account for the chance of failure when deciding what stations to select as a depot for the UAVs. To conduct this demonstration, we take the solutions $S_{0,100}$, $S_{0,99}$, $S_{0,98}$, and put these solutions in a situation where they have a chance of failure—that is, before solving a tornado case, we apply a 5% and 10% chance of failure. The results of these tests can be seen in Table 5.

In our first batch of tests, accounting for failure, the solutions generated by our initial solution method appears to largely match the feasibility goal of the solution. All the solutions are within 1.0% of the feasibility rate.

While using the solutions not accounting for failure there is a minor, yet consistent shortcoming of the solutions not considering depot failure. We see a feasibility drop off 3% versus the solutions accounting for failure and nearly a 4% drop considering the feasibility targets.

**Summary and conclusion**

The problem studied in this article is an application of the location and routing problem where we are trying to determine the choice and location of stations that search teams will be allocated before a tornado disaster. We considered historical weather data and the potential for equipment breakdowns to choose the depots. We also
offered a parameter called “feasibility target” to allow decision-makers to tune and reduce the number of stations in their final solution. This allows for the rare times when the size of the search area (number of waypoints) is so numerous that many more depots are required to ensure adequate coverage in the event of a disaster.

We first demonstrated the relationship between the number of depots in a solution, the chance of depot failure, and a feasibility target. This validates the proposed heuristic (higher depot failures require more depots, lower feasibility targets yield fewer depots) and shows the conservative nature of assuming the need for 100% feasibility (needing 30–80% more stations than even 99% feasibility targets).

Next, we assessed the quality of the solution against unknown tornado cases. When accounting for depot failure, our solutions are within 1% of the target feasibility rates. We also compared the effect of using solutions that do not account for depot failure when depot failure is present. We missed the target feasibility rates by 4% in this case.

There is still plenty of research opportunities. In a sparsely populated state like Oklahoma, most fire stations are volunteer. There could be work on balancing the trade-off between using professional versus volunteer fire stations and/or having differing probabilities for a fire station being ‘down’ as a function of its type or location. In addition, methods could be developed to ensure that station choices do not ‘clump’ together in high station failure rate situations. Stronger methods for generating artificial tornado storms could provide (artificial data sets) could provide better solutions—both in generating the station-location solution as well as testing the station location solution.

**Appendix A: Pseudocode and algorithms**

This appendix contains pseudocode.

**Algorithm 1: Steiner Zone Heuristic**

```python
Steiner Zone Heuristic
Given r_scan -> integer, PointsOfInterest -> list of tuples
groups = set()
random.shuffle(PointsOfInterest) # Puts the PointsOfInterest in a random order
while length(PointsOfInterest) > 0:
    tempGroup = set()
    tempGroup.add(PointsOfInterest.pop()) # selects a random PointsOfInterest
    for point in PointsOfInterest:
        if distanceFunction(point, point2) <= r_scan for all point2 in tempGroup:
            tempGroup.add(point)
            PointsOfInterest.remove(point)
    end if
    end for
    groups.add(tempGroup)
end while
return groups
```

**Algorithm 2: Multi-knapsack inspired initial solution**

```python
Multi-knapsack initial solution generator
Given waypoints -> list of tuples (coordinates), fireStations -> list of tuples (coordinates),
maxKnapsackSize -> float
solution = dict() # Key -> fire station ID, Value -> list of associated waypoints
```
while length(waypoints) >= 0:
    find (station in fireStations, waypoint in waypoints) pair with the minimum
distance between them
    solution[station] = [waypoint, ]
    waypoints.discard(waypoint)
    fireStations.discard(station)
    while sum(distance(station, wpt) for wpt in solution[station]) <= maxKnapsackSize:
        find waypoint2 in waypoints with the minimum distance between the waypoint
        and the station
        solution[station].append(waypoint2)
        waypoints.discard(waypoint)
    end while
end while
return solution

Algorithm 3: Heuristic to solve the location problem

Heuristic to solve the location problem

Given depotFailureRate -> float in [0, 1); targetFeasibilityPct -> float in (0,
1]; allStations -> list of all available fire stations; initialSolution -> list of
stations in initial solution

Parameters maxNumberOfInfeasibleSolutions -> integer on the order of 1000s;
minimumNumberOfGlobalIters -> integer on the order of 3 to 5;
numberOfTestsForEachTornadoEvent -> integer on the order of 10 to 20,
unless depotFailureRate is 0%, then 1 is used; targetTBar -> value that we
desire the UAVs to complete their mission; ScanningDiameter -> 2
times $r_{scan}$

runsCounter = 0
infeasibilityCounter = 0
currentSolution, bestSolution = initialSolution, allStations
newBest = False
while True: # Global Iterations
    while infeasibilityCounter < maxNumberOfInfeasibleSolutions:
        targetFeasibilityTracker = list() # this will be a list of bools
        for each historicalTornadoEvent in historicalTornadoEvents:
            while i < numberOfTestsForEachTornadoEvent:
                i += 1
                operationalStations = GetOperationalStations(currentSolution,
depotFailureRate)
                tBar = GetTBarForEvent(operationalStations,
historicalTornadoEvent, targetTBar, ScanningDiameter)
                if tBar <= targetTBar:
                    targetFeasibilityTracker.append(True)
                else:
                    targetFeasibilityTracker.append(False)
            end while
        end for
        if sum(targetFeasibilityTracker) / len(targetFeasibilityTracker) >=
targetFeasibilityPct: # i.e., feasible solution
            if len(currentSolution) < len(bestSolution):
                newBest = True
            else:
                bestSolution = currentSolution
        else:
Algorithm 4: Getting Event TBar $\bar{T}$

GetTBarForEvent() Algorithm to identify $\bar{T}$

Given operationalStations -> list of stations; historicalTornadoEvent -> list of waypoints associated with a historical tornado event; targetTBar value that we desire the UAVs to complete their mission; ScanningDiameter -> 2 times $r_{scan}$

Waypoints = historicalTornadoEvent.getAssociatedWaypoints()
ExpectedLengthOfAllWaypoints = ScanningDiameter * len(Waypoints)
numStationsNeeded = math.ceil(ExpectedLengthOfAllWaypoints/targetTBar)

while True
    distanceMatrix = [] # create a matrix of all stations in operationalStations to the nearest waypoint in the historicalTornadoEvent
    selectedStations = closest stations in distanceMatrix[ ], i.e., the minimum distances
    dMax = max(D[s in selectedStations])
    if dMax + (ExpectedLengthOfAllWaypoints/numStationsNeeded) <= targetTBar:
        return selectedStations
    else if len(operationalStations) < numStationsNeeded + 1:
        return operationalStations
    else:
        numStationsNeeded += 1

end while

Appendix B: Mathematical Models

Mathematical Model A: Multi knapsack problem

\[
\min \sum_{i \in S} y_i
\]

\[
\sum_{i \in S} x_{ij} = 1 \quad \forall j \in W
\]

\[
\left( \sum_{j \in W} d_{ij} x_{ij} \right) - Ky_i \leq 0 \quad \forall i \in S
\]

\[
y_i \in \{0, 1\} \quad \forall i \in S \quad x_{ij} \in \{0, 1\} \quad \forall i \in S, j \in W
\]

Where $i \in S$ is the collection of stations (knapsacks), $j \in W$ is the collection of waypoints (items), $d_{ij}$ is the distance metric from station $i$ to waypoint $j$ (the weight of putting item $j$ in knapsack $i$), $K$ is the capacity of the stations (capacity of the knapsacks). The binary variable $y_i$ takes the value of 1 if station $i$ is used, 0 otherwise. The binary variable $x_{ij}$ takes the value of 1 if waypoint $j$ is assigned to station $i$, 0 otherwise. The objective function (1) consists in minimizing the number of stations, the first constraint (2) ensures each waypoint is assigned
to a station, the second set of constraints (3) links the stations to the waypoints and sets the maximum number of waypoints that can be assigned to each station. The last set of constraints (4) defines both \( y_i \) and \( x_{ij} \) as binary variables.

**Appendix C: Data Locations**

| Data                                              | Location                                      | Notes                                         |
|---------------------------------------------------|-----------------------------------------------|-----------------------------------------------|
| Storm Based Warnings (SBWs) and Local Storm Reports (LSRs) | https://mesonet.agron.iastate.edu/           | Weather Forecast Offices: OUN, TSA, AMA, SHV  |
| Simplified tornado tracks                         |                                               | Dates:                                        |
| Road data for the state of Oklahoma               | https://www.spc.noaa.gov/gis/svrgis/          | ODOT Local Roadways                           |
|                                                   | https://okmaps.org/ogi/search.aspx            | ODOT Roadways                                 |
|                                                   |                                               | ODOT Highways                                 |
|                                                   |                                               | Oklahoma Fire Stations                        |

**Appendix D: Notation and Acronyms**

| Notation | Meaning                           | Definition                                                                 |
|----------|-----------------------------------|---------------------------------------------------------------------------|
| LSR      | Local Storm Report                | A visual identification of a storm occurring                              |
| NWS      | National Weather Service          | The United States’ agency for weather forecasts                             |
| SAR      | Search and Rescue                 | Storm Based Warnings will show the specific meteorological or hydrological threat area and are not restricted to geopolitical boundaries. In this article they delineate the area a UAV will conduct a search |
| SBW      | Storm Based Warning               |                                                                          |
| tBar or  | In a vehicle routing problem, the tBar indicates the longest route taken in a collection of routes |
| UAV      | Unmanned Aerial Vehicle           |                                                                          |

**Note**

1. While we store all feasible solutions, we do not use it in any further computations.

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