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# Bi-objective capacitated facility location problem with range constrained drones

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ABSTRACT. Given a set of demand and potential facility locations and a set of fully available charged drones, an agency seeks to locate a pre-specified number of capacitated facilities and assign drones to the located facilities to serve the demands. The facilities serve as drone launching sites for distributing the resources. The formulation captures the vehicle-drone routing interactions during the drone dispatching and collection processes and accounts for drone operation constraints related to flight range and load carrying capacity limitations. Each drone makes an one-to-many- to-one trip from the facility location to the demand points and back until the battery range is met. The planning period is short-term and therefore the recharging of drone batteries is not considered. In this paper, we developed a bi-objective model for minimizing the total facility construction and transportation costs and maximizing the total demand coverage. Furthermore, the bi-objective model is solved by e-constraint method. We consider the second objective function as a constraint.

## 1. INTRODUCTION

Last mile logistics has become a popular area of interest for retailers. Companies are always searching for fast and cost-efficient ways to deliver goods to their customers. Several companies like Amazon, Google, UPS, and Flytrex are evaluating the potential use of Unmanned Aerial Vehicles (UAVs) or drones for commercial service or package deliveries [1]. Drones are not restricted by the availability of existing infrastructure and therefore can lead to improved last-mile efficiency, safety, and reliability. Drones are particularly suitable for emergency applications like search and rescue [1], deliveries of critical medical supplies post-disaster or for emergency response.

routing and scheduling leading to several interesting variants of the traveling salesman and vehicle routing problems. Murray and Chu [7] studied the flying sidekick traveling salesman problem (FSTSP) where a drone and a truck deliver in collaboration to a set of customers. The drone takes-off from the truck, makes the delivery, and rendezvous back with the truck at a different location. Murray and Chu [7] also proposed the parallel drone scheduling traveling salesman problem (PDSTSP) where a set of UAVs and a truck make deliveries from a single depot to customers. Agatz et al. [1] denoted the FSTSP as Traveling Salesman Problem with Drones (TSPD). Ha et al. [6] focused on the min-cost TSPD variant of Murray and Chu [7] FSTSP and developed a greedy randomized adaptive search procedure which builds TSPD routes from TSP routes. Dayarian et al. [4] studied the dynamic and multiple vehicles and drones variant of Murray and Chu [7] PDSTSP. In contrast to the above works, Chauhan et al. [3] consider a drone only delivery system and do not consider truck deliveries as this is the case for medical supplies. They proposed an integer linear programming formulation with the objective of maximizing coverage while explicitly incorporating the drone energy consumption and

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range constraints. We developed a bi-objective model for minimizing the total facility construction and transportation costs and maximizing the total demand coverage. nowadays facility construction and transportation costs are in important issue for companies that has not been addressed in other articles. we considered the total facility construction and transportation costs and developed the bi-objective model for minimizing the total facility construction and transportation costs and maximizing the total demand coverage. We also model the distance range constraints that is dependent in battery capacity.

## 2. Problem formulation

This section presents the integer linear programming formulation for facility location problem with range constrained drones. At the beginning of the planning period, an agency is given a set of demand locations I each having demand $\boldsymbol{wi}$, a set of potential facility locations J and set of available fully-charged drones $\boldsymbol{K}$. the agency's goal is to locate $\boldsymbol{P}$ facilities to maximize the demand served and minimize the total cost. The agency will allocate resource of mass $\boldsymbol{uj}$ can be viewed as the capacity of the facility. The capacity of a facility corresponds to the maximum amount of demand which can be served from that facility in a period of time. The limiting factor for the capacity in practice would arise from the maximum mass of resources which can be stored at each facility, equipment and building characteristics, staffing levels, etc. The agency will also assign drones to each open facility. The facilities serve as drone launching sites for distributing the resources while respecting the facility capacity and drone range constraints. In this paper, we consider the cost of transportation of packages and drones from warehouses to these locations. We also assume that the demand during each planning horizon is smaller than the capacity of each drone. As we are looking at a relatively small time frame, we do not consider recharging of drone batteries during the planning period. We assume that the drone batteries are recharged overnight or in-between planning periods [5]. The notation used in the formulation is given below.

### Sets

$\boldsymbol{I}$ Set of all demand locations indexed by $\boldsymbol{i}$
$\boldsymbol{J}$ Set of all potential facility locations indexed by $\boldsymbol{j}$
$\boldsymbol{K}$ Set of available drones indexed by $\boldsymbol{k}$
$\boldsymbol{S}$ The set of disruption events

### Parameters

$\boldsymbol{fj}$ The construction cost of facility $\boldsymbol{j}$
$\boldsymbol{cij}$ Unit-price of transportation from the facility j to demand $\boldsymbol{i}$
$\boldsymbol{dij}$ Travel distance between demand point i and facility $\boldsymbol{j}$
$\boldsymbol{wi}$ Demand at location $\boldsymbol{i}$
$\boldsymbol{uj}$ Capacity of each located facility $\boldsymbol{j}$
$\boldsymbol{oij}$ The added costs from facility $\boldsymbol{j}$ to demand $\boldsymbol{i}$ when workers predict the nonoccurrence of a disruption event, which consequently occurs
$\boldsymbol{lij}$ The added costs when workers predict the occurrence of a disruption event and the forecast costs from facility $\boldsymbol{j}$ to demand $\boldsymbol{i}$
$\boldsymbol{p}$ Maximum number of facilities
$\boldsymbol{fj}$ $\boldsymbol{q} \in [0;\ 1]$ is the ratio between the transportation costs and the added prediction costs on the occurrence of a disruption event.
$\boldsymbol{B}$ Battery capacity of each drone
$\boldsymbol{\beta}$ The amount of energy consumed in a distance unit
$\boldsymbol{ms}$ 1 if disruption event occurrence 0 otherwise($\forall s \in S$)
$\boldsymbol{vijs}$ 1 if disruption event(s) occurrence is predicted 0 otherwise ($\forall i \in I$; $\forall j \in J$; $\forall s \in S$)

## Decision variables

***xijk*** 1, if customer i ∈ I is served by the kth drone of plant j ∈ J, and 0 otherwise
***yj*** 1, if the facility is located at j ∈ J , and 0, otherwise
***zjk*** 1, if the kth drone is assigned to facility j ∈ J , and 0, otherwise.

$$(1) \quad \min \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} w_i x_{ijk}$$

$$(2) \quad \min \sum_{j\in J} f_j y_j + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} c_{ij} d_{ij} w_i x_{ijk} + \sum_{i\in I}\sum_{j\in J}\sum_{s\in S}(v_{ijs} l_{ij} + (1 - v_{ijs}) o_{ij} m_s)$$

$$(3) \quad s.t \sum_{j\in J}\sum_{k\in K} x_{ijk} \le 1, \qquad \forall i \in I$$

$$(4) \quad \sum_{j\in J} y_j \le p,$$

$$(5) \quad z_{jk} \le y_j, \qquad \forall j \in J, \forall k \in K$$

$$(6) \quad \sum_{j\in J} z_{jk} \le 1, \qquad \forall k \in K$$

$$(7) \quad \sum_{i\in I}\sum_{k\in K} w_i x_{ijk} \le u_j y_j, \qquad \forall j \in J$$

$$(8) \quad \sum_{i\in I} \beta d_{ij} x_{ijk} \le B z_{jk}, \qquad \forall j \in J, \forall k \in K$$

$$(9) \quad l_{ij} \le q c_{ij} d_{ij} w_i, \qquad \forall j \in J, \forall i \in I$$

$$(10) \quad x_{ijk}, y_j, z_{jk} \in [0, 1], \qquad \forall i \in I, \forall j \in J, \forall k \in K$$

The objective (1) is to maximize the demand served. The objective (2) is to minimize the total facilities construction and transportation costs. Constraint (3) ensures that each demand location is covered at most once. Eq. (4) restricts the number of facilities located to be less than or equal to p. Constraint (5) ensures that vehicles are assigned only to located facilities. Constraint (6) ensures that each drone is assigned to at most one open facility. Constraint (7) forces the demand served by each located facility to be less than or equal to the capacity of the facility. Constraint (8) enforces battery range constraints on all the drones. Constraint (9) ensures that the prediction cost is no more than half the transportation cost. Constraint (10) corresponds to variable definition constraints and forces all decision variables to be binary.
There exist several solution methods that have been proposed for bi-objective programming. They can be classiffied to five main categories: scalar methods, interactive methods, fuzzy methods, meta-heuristic methods, and decision aided methods [2 and 8]. The conventional bi-objective optimization techniques widely used in practice including -constraint, weighted sum, weighted metric, goal programming and lexicographic, etc. Haimes et al.[6] presented the $\epsilon$-constraint method, they proposed that one of the objective functions is optimized while other objective functions are converted into constraints with allowable bounds. The problem is stated as follows:

$$\begin{aligned} &min\ z_k(x) \\ &\text{s.t} \quad z_i(x) \le \varepsilon_i, \quad i \ne k, \ x \in X, \end{aligned}$$

Therefore, a set of Pareto-optimal solutions can be obtained by changing the values of $\varepsilon$.

## 3. Main results

Example 3.1. let $|I| = 5$, $|J| = 4$, $|K| = 3$, $|S| = 1$, $p = 3$, $\beta = 2$, $q = .5$, $B = 100$.

$$c_{11} = 2, c_{12} = 3, c_{13} = 2, c_{14} = 3, c_{21} = 3, c_{22} = 4, c_{23} = 3, c_{24} = 4, c_{31} = 2, c_{32} = 3$$
$$c_{33} = 2, c_{34} = 3, c_{41} = 4, c_{42} = 5, c_{43} = 4, c_{44} = 5, c_{51} = 5, c_{52} = 6, c_{53} = 5, c_{54} = 6$$

$$d_{11} = 3, d_{12} = 5, d_{13} = 7, d_{14} = 8, d_{21} = 4, d_{22} = 7, d_{23} = 8, d_{24} = 10, d_{31} = 5, d_{32} = 8,$$
$$d_{33} = 9, d_{34} = 11, d_{41} = 4, d_{42} = 5, d_{43} = 4, d_{44} = 5, d_{51} = 7, d_{52} = 10, d_{53} = 11,$$
$$d_{54} = 13$$

$$U = (u_j) = [80;\ 150;\ 60;\ 45], W = (w_i) = [35;\ 40;\ 25;\ 25;\ 10]$$

$$L = (l_{ij}) = O = (o_{ij}) = C = (c_{ij}), F = (f_j) = [80;\ 150;\ 60;\ 45], v_{111} = 1$$

We assume that "2 = 2000 and solve this example at aimms and obtain

$$y1 = 1, y3 = 1, z11 = 1, z32 = 1, x332 = 1, x532 = 1, x111 = 1, x211 = 1, Z1 = 80.$$

## 4. Conclusions

Today the cost of building facilities is an important issue for companies that have not been taken into consideration, and only transportation costs have been taken into account without taking into account the distributiond disruption. in this paper, we developed a bi-objective model for minimizing the total facility construction and transportation costs and maximizing the total demand coverage. also the distributiond disruption is seen as distribution risk as distribution disruption events are unplanned. As real-world drone-based deliveries have already started being implemented in the field, it is necessary to study facility location for drones not only for economic purposes but also for social/humanitarian benefit. Drone deliveries tend to be time-sensitive, e.g. medical supplies, and or subject to unexpected changes in weather conditions. Hence, solution times are as important as solution quality. In this research the bi-objective model is solved by e-constraint method. We consider the second objective function as a constraint and solve it at aimms.

## REFERENCES

1. *N. Agatz, P. Bouman, M. Schmidt. Optimization approaches for the traveling salesman problem with drone, Transp. Sci, (2018)*

2. *Y. Collette, P. Siarry. Multiobjective optimization: principles and case studies, Springer Science and Business.*

3. *Ch. Darshan, A. Unnikrishnan, and M. Figliozzi. Maximum coverage capacitated facility location problem with range constrained drones, Transportation Research Part C: Emerging Technologies, 99(2019), 1-18.*

4. *I. Dayarian, M. Savelsbergh, J. P. Clarke. Same-day delivery with drone resupply, Optimization online.*

5. *Yu. G, Qi. X. Disruption management: framework, models and applications, World Scienti_c Publishing Company Incorporated, Singapore, (2004).*

6. *Y. Y. Haimes, L. S. Ladson, and D. A. Wismer, Bi criterion formulation of problems of integrated system identi_cation and system optimization, . IEEE Transactions on Systems Man and Cybernetics, (3), 296 (1971).*

7. *C. C. Murray, A. G. Chu. The ying sidekick traveling salesman problem: optimization of drone-assisted parcel delivery, Transp. Res. Part C: Emerg. Technol, 54 (2015), 86-109.*

8. *M. Rajabi-Bahaabadi, A. Shariat-Mohaymany, M. Babaei, and C. W, Ahn, Multi-objective path _nding in stochastic time-dependent road networks using non-dominated sorting genetic algorithm, Expert Systems with Applications, 42(12) (2015) 5056-5064.*

9. *Z. Wang, Hu. XP, Wang. XP. Disruption management model and algorithm for distribution vehicle scheduling problems under accidental travel time delay, Syst Eng Theory Practice, 33((2)) (2013), 378.*