Addressing the Challenges of Last-mile: The Drone Routing Problem with Shared Fulfillment Centers

Maria Elena Bruni and Sara Khodaparasti

Department of Mechanical, Energy and Management Engineering, University of Calabria, Rende, Cosenza, Italy

Abstract: With the easing of restrictions worldwide, drones will become a preferred transportation mode for last-mile deliveries in the coming years. Drones offer, in fact, an optimal solution for many challenges faced with last-mile delivery as congestion and emissions and can streamline the last leg of the supply chain. Despite the common conviction that drones will reshape the future of deliveries, numerous hurdles prevent practical implementation of this futuristic vision, among which the limited drone range and payload. To overcome this issue, big companies such as Amazon, are already filing up patents for the development of fulfilment centers where drones can be restocked before flying out again for another delivery, effectively extending their range. Only a few authors have addressed the joint problem of operating these facilities and providing services to retail companies. This paper addresses this problem and proposes a mathematical formulation to show the viability of the proposed approach.

1 INTRODUCTION

The last few years have seen a sharp increase of the paradigms of on-demand economy and e-commerce. To catch up with these trends, new last-mile delivery systems, exploiting the use of drones, have been envisioned to reduce delivery times, avoid traffic delays and potentially cut costs in the long term.

Although drones are used in a number of applications within logistics and delivery, this ambitious program has yet to be implemented on a large scale. The vision of drone-based last-mile solutions, within a fully automated delivery system, is challenged by intrinsic characteristic as small payload, limited battery capacity and regulatory and safety issues of air control administrations. Despite these unsolved questions, the idea of using drones for parcel delivery is gaining ground. We should hence expect that, in a near future, these types of delivery systems will be more common for products and services and there will be greater adoption of this technology. In preparation for this possible future, Amazon released a number of patents for different types Fulfillment Centers (FCs) that would accommodate the landing and takeoff of drones in dense urban settings. These stations, networked with a central control and a plurality of drones, include a number of services from package handling to recharging/refueling operations. This raises emerging problems relative to the location of new, maybe big, FCs closer to customers and the management of delivery services provided. A possible promising solution for enhancing the use of drones in the last-mile, is the adoption of a shared use of FCs among retail companies providing drone delivery services. As a matter of facts, sharing FCs could sensibly reduce the total number of drones in the sky and the total operational costs of companies. This paradigm, dealing with the complexity of the sharing economy, raises significant challenges to policy and decision-makers, as well as operational issues to be addressed.

This paper takes a step in this direction, providing a guide to retail companies for drone routing and FCs choice, to better control the whole process, offering practical insights on how to to manage this new system. The problem is complicated, since it merges complexity of a combined location-routing problem with new operational challenges related to the use of drones, among which energy consumption—which nonlinearly depends on the payload, battery weight, and travel time— and uncertainty in flight duration. The remainder of this paper is organized as follows. Section 2 provides a detailed review of the relevant literature. The problem under study is described in Section 3. In Section 4, computational results are discussed. Finally, Section 5 presents conclusions and directions for future research.

2 LITERATURE REVIEW

To put the contribution of the present paper in the right stream, we restrict our attention to routing problems where drones are used to directly deliver parcels to customers.

A pure drone delivery problem was addressed in (Dorling et al., 2016), where two multi-trip vehicle routing formulations differing only in terms of the objective function (either total operating cost or total delivery time) were proposed. A simulated annealing algorithm was designed to solve the model heuristically. A package delivery problem with autonomous drones considering the battery capacity and its relation with payload and flight range was considered in (Choi and Schonfeld, 2017). The objective function was expressed as the total cost including the cost associated to the estimated users' waiting time. In another study, the drone delivery problem was addressed in a multi-trip context (Troudi et al., 2018), where the minimization of total travel distance, drone fleet size, and number of batteries is considered. All the previous contributions failed to take into account the nonlinear nature of the energy constraints, hampering in this way the successful application of drone-based delivery systems. An important exception is a recent paper (Cheng et al., 2020), where the multi-trip drone routing problem is formulated as a two-index model, and the energy consumption depends nonlinearly on the payload and linearly on travel distance. Some valid cuts are presented and a branch-and-cut algorithm is developed. (Kim et al., 2021) proposed a drone routing model with multiple depots and multiple drones, with flight range constraints. The objective function minimizes the sum of routing and drone usage costs. Following the location routing context, in (Kim et al., 2017) the use of drones for a pickup and delivery problem arising in healthcare is investigated. The authors proposed a set covering model to find the optimal number of locations used as depots, followed by a multi-depot drone routing model. A Lagrangian Relaxation method was also proposed to solve the model. Another applicative context of drone location routing is patrol application (Liu et al., 2019). The model finds the optimal location of sites to launch the drones and the optimal drone routes minimizing the total cost, including the base establishment cost, drone usage cost, and the flight cost. (Torabbeigi et al., 2020) proposed two mathematical formulations involving strategic and operational plans to optimize the drone routes for parcel delivery. At the strategic level, a set covering model is solved to determine the minimum number of depots to open such that all customers are covered; next, at the operational stage, a drone routing model is solved in order to find the minimum number of required drones to dispatch from the open depots and the corresponding optimal drone paths. The authors include energy consumption constraints into the problem and model them as a linear functions in terms of payload and travel time.

3 MATHEMATICAL FORMULATION

We introduce in this section the Drone Routing Problem with Shared FCs (DRP-ShaFC) as a tailored location-routing problem, where the operational challenges related to the use of drones, among which energy consumption and uncertainty in flight duration, are taken into account. Our model also includes, rather originally, a latency objective, i.e. the sum of arrival times at the customers, which is a compelling measure for customer-oriented problems, where customers' demand should be met in a timely fashion.

We assume that a set D of distributed FCs are available to be used to enhance last-mile delivery. We can consider any type of FCs, truck-based warehouses, local re-stocking stations for drones or beehives as well. To offer landing, takeoff, package handling, recharging services, the FC operator requires a tariff (in the foregoing denoted by T).

A retail company owning k drones, should bring items to a set C of customers on the ground. Each drone makes multiple stops per trip: a single trip consists of the drone starting at a given FC, where it would be loaded with the customers' orders up to its payload capacity Q, and visiting one or more customers. At the end of each flight, the drone is sent back to one of the FCs, not necessarily the same of the departure.
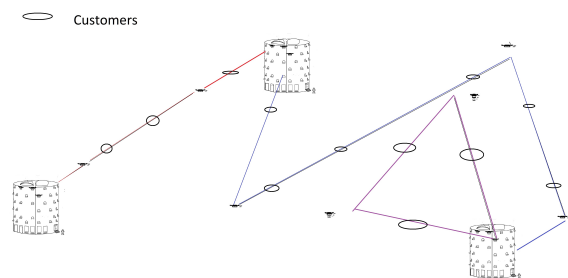

Figure 1: Scheme of the delivery system.

Figure 1 represents the delivery scheme. The drone energy consumption between the FCs and the delivery points determines the optimal delivery route based on the battery capacity. Instead of assuming that drone endurance is limited by a fixed flight
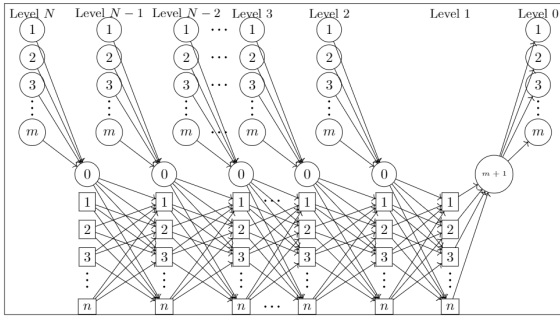
Figure 2: Multi-layer network.

time, we consider energy consumption as a (nonlinear) function of payload, battery weight, and travel time. In particular, let t_{ij} be the travel time between nodes i and j, $W + M = \Gamma$ (W is the frame weight (in kg) and M (kg) is the battery weight). The energy consumed by the drone, carrying a payload d_i is expressed as $k(\Gamma + d_i)^{3/2} t_{ij}$ where $k = \sqrt{\frac{g^3}{\rho \xi h}}$ (here g is the gravity constant (in N), ρ is the fluid density of air (in kg/m^3), ξ is the area of spinning blade disc (in m^2) and h is the number of rotors) (Cheng et al., 2020).

The mathematical formulation is essentially developed based on an extension of the multi-layer network, which has been proved to be superior to other models, for a wide range of routing problems (for more information, please see (Nucamendi-Guillén et al., 2016), (Bruni et al., 2020)).

The multi-layer network is displayed in Figure 2 where the customers and the FCs are depicted by squares and circles. The auxiliary FCs 0 and $m + 1$ are added to specify, respectively, the start and the end of each tour. The network contains $N + 1$ levels (positions) where $N = |C| - k + 1$ is an upper bound on the number of visited customers in a tour. Let $L = \{0, \cdots, r, \cdots, N\}$ be the set of levels. Levels N to 2 represent the position of the visited customer within the tour and include copies of customers, FCs and the auxiliary FC 0. Instead level 1 corresponds to the last visited customer within the drone trip and includes only copies of customers and of the auxiliary FC $m + 1$. For the sake of completeness we also consider level 0 to specify the FC that retrieves the drone. A feasible solution in the multi-layer network is made of k distinct drone trips where each trip starts from a copy of one of the FCs, that is directly linked to the auxiliary FC 0, and is followed a subset of customers. The last visited customer is the one followed by the auxiliary FC $m + 1$ that is directly connected to the Fcs that retrieves the drone. Based on the structure of the multi-layer network, we define two set of position dependent binary variables: x_i^r, $i \in C$ which indicate if customer i is visited in position r (meaning

that is the rth-last one), y_{ij}^r, $r \geq 1$ to show that customer j is visited right after node $i \in D \cup C$ in position r and w_{ij}^r, $r \geq 2$ which tell if customer j is the first one to be visited by a drone launched from the FC $i \in D$ and there are $r - 1$ customers to be visited in the trip. We also extend the definition of variables y and w to account for the end of each drone trip where $y_{j(m+1)}^0$, $j \in C$ takes 1 if the customer j is the last stop of the trip drone, and therefore is followed by the dummy FC $m + 1$; also, w_{ji}^1, $j \in C$, $i \in D$ takes 1 if after serving the last customer j, the drone is retrieved at the FC i. Binary variables z_i indicate if the FC i is used or not. The total load carried by the drone upon departure from customer i to reach customer j is denoted by u_{ij}; if customer j is the first customer after the drone departure from the FC f, its load is denoted by v_{fj}. The accumulated energy consumption upon arrival at node $i \in C \cup D$ is denoted by e_i. Let define $V = D' \cup C \cup D$, where $D' = \{0, m + 1\}$ is the set of auxiliary FCs introduced to specify the start and the end of each drone trip. The total number of FCs used is limited to N_s and each FC $i \in D$ can host at most N_d^i drones. Using the above notation, the model is formulated as

$$\min \sum_{i \in D} \sum_{j \in C} \sum_{\substack{r \in L \\ r \neq 1}} r t_{ij} w_{ij}^r + \sum_{i \in C} \sum_{\substack{j \in C \\ j \neq i}} \sum_{r \in L} r t_{ij} y_{ij}^r + \sum_{i \in D} T_i z_i \quad (1)$$

$$\sum_{r \in L} x_i^r = 1 \quad i \in C \quad (2)$$

$$\sum_{r \in L} \sum_{j \in C} y_{0j}^r = k \quad (3)$$

$$\sum_{i \in C} x_i^1 = \sum_{r \in L} \sum_{j \in C} y_{0j}^r \quad (4)$$

$$\sum_{\substack{j \in C \\ j \neq i}} y_{ij}^r = x_i^{r+1} \quad i \in C, r \in L \setminus \{N\} \quad (5)$$

$$\sum_{\substack{i \in C \cup \{0\} \\ i \neq j}} y_{ij}^r = x_j^r \quad j \in C, r \in L \setminus \{N\} \quad (6)$$

$$y_{0j}^N = x_j^N \quad j \in C \quad (7)$$

$$\sum_{i \in D} w_{ij}^r \geq y_{0j}^r, \quad j \in C, r \in L \setminus \{1\} \quad (8)$$

$$z_i \geq w_{ij}^r, \quad i \in D, j \in C, r \in L, \setminus \{1\} \quad (9)$$

$$\sum_{i \in D} z_i \leq N_s \quad (10)$$

$$\sum_{j \in C} \sum_{r \in L} w_{ij}^r \leq N_d^i \quad i \in D \quad (11)$$

$$x_j^1 = \sum_{i \in D} y_{j(m+1)}^0 \quad j \in C \quad (12)$$

$$y_{j(m+1)}^0 \geq \sum_{i \in D} w_{ji}^1 \quad (13)$$

$$\sum_{j \in C} w_{ji}^1 \leq \sum_{r \in L \setminus \{1\}} \sum_{j \in C} w_{ij}^r \quad i \in D \quad (14)$$

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$$v_{ij} \geq d_j \sum_{r \in L \setminus \{1\}} w_{ij}^r, \ i \in D, j \in C \tag{15}$$

$$v_{ij} \leq Q \sum_{r \in L \setminus \{1\}} w_{ij}^r, \ i \in D, j \in C \tag{16}$$

$$u_{ij} \geq d_j \sum_{r \in L} y_{ij}^r, \ i, j \in C, i \neq j \tag{17}$$

$$u_{ij} \leq (Q - d_i) \sum_{r \in L \setminus \{N\}} y_{ij}^r, \ i, j \in C, i \neq j \tag{18}$$

$$\sum_{h \in D} v_{hi} + \sum_{\substack{j \in C \\ j \neq i}} u_{ji} - \sum_{\substack{j \in C \\ j \neq i}} u_{ij} = d_i, \ i \in C \tag{19}$$

$$e_i + k(\Gamma + u_{ij})^{3/2} t_{ij} \leq e_j + M'_{ij}(1 - \sum_{\substack{r \in \\ L \setminus \{N\}}} y_{ij}^r) \ i, j \in C, i \neq j \tag{20}$$

$$e_i + k(\Gamma + v_{ij})^{3/2} t_{ij} \leq e_j + M''_{ij}(1 - \sum_{\substack{r \in \\ L \setminus \{1\}}} w_{ij}^r) \ i \in D, j \in C \tag{21}$$

$$e_j + k\Gamma^{3/2} \sum_{i \in D} t_{ji} w_{ji}^1 \leq B \ j \in C, i \in D \tag{22}$$

$$e_i = 0 \ i \in D \tag{23}$$

$$z_i \in \{0, 1\} \ i \in D \tag{24}$$

$$x_i^r \in \{0, 1\} \ i \in C, r \in L \tag{25}$$

$$y_{0j}^r \in \{0, 1\} \ j \in C, r \in L \tag{26}$$

$$y_{j(m+1)}^0 \in \{0, 1\} \ j \in C \tag{27}$$

$$y_{ij}^r \in \{0, 1\} \ i, j \in C, i \neq j, r \in L, r \neq N \tag{28}$$

$$w_{ij}^r \in \{0, 1\} \ i \in D, j \in C, r \in L \setminus \{1\} \tag{29}$$

$$w_{ij}^1 \in \{0, 1\} \ i \in C, j \in D \tag{30}$$

$$u_{ij} \geq 0 \ i, j \in C, i \neq j \tag{31}$$

$$e_i \geq 0 \ i \in D \tag{32}$$

where M'_{ij} and M''_{ij} are the "big-M" parameters.

The objective function (1) minimizes the total waiting times of the customers plus the cost associated to the use of the FCs. Constraints (2) ensure that each customer is visited exactly once. Constraint (3) ensures the use of exactly k drones. Constraint (4), (5) and (6) guarantee the continuity of each tour. Constraints (7) force nodes to be connected to node 0 at level N. Constraints (8) and (9) allow starting a drone route only from used facilities. Constraint in (10) and (11) represent the restriction on the maximum number of facilities used and the number of drones that each facility can handle. Constraints (12)-(13) define the relation between the last customer visited and the destination facility. Constraints (14) determine the return of drones to facilities. Constraints (15)–(19) are used to limit the drone payload (Nucamendi-Guillén et al., 2018). Constraints (20)–(23) represent the drone energy consumption. Finally, Constraints (24)–(32) establish the nature of the variables.

As known, weather conditions, wind direction and aerial congestion can influence the travel time of the drone and hence, the energy consumption. In this paper, we consider drone travel time as an uncertain parameter belonging to a box uncertainty $U_\infty = \{\xi | \|\xi\|_\infty \leq \Psi\}$, where here Ψ is a parameter controlling the size of the uncertainty set.

Following the robust paradigm in (Ben-Tal et al., 2015), the robust counterpart of the proposed model can be derived as follows.

$$\min \sum_{\substack{r \in L \\ r \neq 1}} r(\bar{t}_{ij} + \Psi \hat{t}_{ij}) w_{ij}^r + \sum_{i \in C} \sum_{\substack{j \in C \\ j \neq i}} \sum_{r \in L} r(\bar{t}_{ij} + \Psi \hat{t}_{ij}) y_{ij}^r + \sum_{i \in D} T_i z_i \tag{33}$$

$$e_i + k(\Gamma + u_{ij})^{3/2}(\bar{t}_{ij} + \Psi \hat{t}_{ij}) \leq e_j + M'_{ij}(1 - \sum_{r \in L \setminus \{N\}} y_{ij}^r)$$
$$i, j \in C, i \neq j \tag{34}$$

$$e_i + k(\Gamma + v_{ij})^{3/2}(\bar{t}_{ij} + \Psi \hat{t}_{ij}) \leq e_j + M''_{ij}(1 - \sum_{r \in L \setminus \{1\}} w_{ij}^r)$$
$$i \in D, j \in C \tag{35}$$

$$e_j + k\Gamma^{3/2} \sum_{i \in D} (\bar{t}_{ji} + \Psi \hat{t}_{ji}) w_{ji}^1 \leq B \ j \in C, i \in D \tag{36}$$

(2)-(19), (23)-(32)

where the uncertain parameter t_{ij} falls within the symmetric box $[\bar{t}_{ij} - \Psi \frac{\hat{t}_{ij}}{2}, \bar{t}_{ij} + \Psi \frac{\hat{t}_{ij}}{2}]$.

4 COMPUTATIONAL EXPERIMENTS

In this section, we conduct some experiments to show the validity of the proposed formulation.

All the experiments were executed on an Intel Core i7-10750H, with 2.60 GHz CPU and 16 GB RAM working under Windows 10 with the algebraic modeling language AIMMS 4.79.2.5. Since model (1)–(32) is a nonlinear MIP model with box uncertainty set, we solved it using the outer approximation algorithm with a time limit of 500 seconds. The Outer approximation algorithm is considered as the state-of-the-art approach for solving MINLP models. The algorithm follows a basic decomposition approach and solves an alternating sequence of nonlinear subproblems and relaxed MIP master problems that provide, respectively, upper and lower bounds. If the original MINLP model is convex, the algorithm guarantees to find the global optimal solution (Duran and Grossmann, 1986). We used the A1 and A2 instances presented in (Cheng et al., 2020). The demand distribution varied between values from [0.1, 0.7] kg for the first 40% of customers and from [0.1, 1.5] kg for the remaining customers. Two configurations (Centeres and Marginal) were selected for the FCs locations, either in the center of the customers area or in the outskirts. In the problem analysis, values of 2,3,5,6 were chosen as the maximum number of drones per

Table 1: Results for Set A1 instances.

					Centered		Marginal	
Instance	$|C|$	$|D|$	k	N_d	Obj	CPU (s)	Obj	CPU (s)
A_10_1	10	5	2	2	7.016	7.09	6.635	2.85
A_10_2					6.796	2.02	6.557	2.68
A_10_3					6.838	4.11	NFS	500
A_10_4					6.568	2.77	N.A.	N.A.
A_10_5					6.956	2.75	NFS	500
A_15_1	15	5	3	2	12.09	33.38	12.05	35.1
A_15_2					12.524	48.49	12.252	30.17
A_15_3					11.999	37.94	12.127	32.12
A_15_4					12.241	42.86	12.346	41.78
A_15_5					12.327	47.55	11.873	51.74
A_20_1	20	5	4	3	12.602	336.83	12.591	305.37
A_20_2					12.667	442.88	12.559	440.93
A_20_3					12.68	496.25	12.684	425.31
A_20_4					-	500	-	500
A_20_5					-	500	-	500
Avg						166.99		257.87

Table 2: Results for Set A2 instances.

					Centered		Marginal	
Instance	$|C|$	$|D|$	k	N_d	Obj	CPU (s)	Obj	CPU (s)
A2_10_1	10	5	2	2	6.901	2.51	6.759	2.16
A2_10_2					6.712	2.68	-	500
A2_10_3					6.787	2.05	-	500
A2_10_4					6.808	2.13	N.A.	N.A.
A2_10_5					6.795	2.57	-	500
A2_15_1	15	5	3	2	12.11	37.94	12.165	30.95
A2_15_2					12.035	34.72	12.032	30.43
A2_15_3					11.934	22.27	11.795	26.58
A2_15_4					12.313	47.91	12.247	41.05
A2_15_5					12.108	20.58	12.342	20.6
A2_20_1	20	5	4	3	12.312	302.21	12.791	273.28
A2_20_2					12.625	452.68	12.163	434.08
A2_20_3					12.425	451.64	12.561	403.01
A2_20_4					-	500	-	500
A2_20_5					-	500	-	500
Avg						158.79		284.14

FC. The tariff for using a FC has been set according to (Aurambout et al., 2019) as the potential average cost across the whole industry, inclusive economies of scales multiplied by the average number of customers serviced. We remark that in the considered experiments the FC tariff has been considered independent from the specific location. In fact, given the limited drone range, the more the FCs are close to the customers, the higher will be the number of companies willing to use the service. Even though the FC building cost is higher as we approach the city center, it is also true that the massive use of the service by commercial companies could lower the tariffs, given that the FC economic return is higher. Hence, considering the same tariff for both configurations is, in our opinion, reasonable.

Finally, we considered a homogeneous fleet of 2, 3, 4, 7 or 8 Alta 8 drones with the following characteristics: $W = 6.2\,(kg), M = 2.8\,(kg), h = 8, \rho = 1.204\,(kq/m^3), \xi = 0.1256\,(m^2), B = 0.355\,(kWh)$.

Tables 1 and 2 present the characteristic of the instances considered, the objective function value (Obj) and the solution time in seconds (CPU) for set A1 and A2. As a general observation, we note that the com-
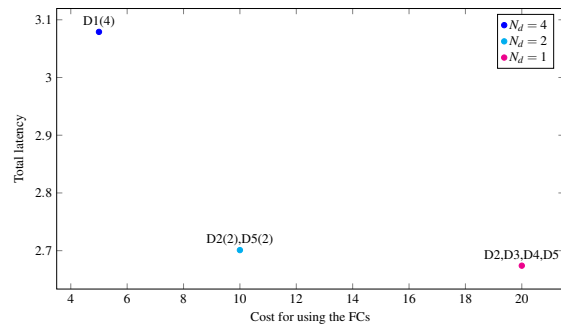

Figure 3: Trade-off between latency and cost.

putational time is quite limited, especially considering that this problem is a tactical operational problem. For some instances, however, it was not possible to find a solution within 500 seconds (a dash is reported in the Tables). The position of the FCs does not seem to influence a lot the total latency since on average the percentage difference is quite low and below 5%. We notice, however that one instance (A1_10_4) becomes infeasible when the FCs are marginally placed in the customer's area.

Figure 3 shows the impact of the number of drones that each FCs can dispatch. As it is evident, to quickly satisfy the delivery demand it is beneficial for the delivery company to use more FCs. We observe that the total latency could decrease from around 3 hours to 2.6 hours. However, the cost for using the FCs can considerably increase.

5 CONCLUSIONS

In this paper, we addressed a new emerging problem in last-mile logistics, namely the joint management of FCs and autonomous vehicles. The process is modeled as a variant of the location routing problem, called DRP-ShaFC. The main characteristics of this new problem are the drones intrinsic properties, as a limited battery capacity, payload, and the weather-related uncertainties that lead to uncertain flight duration. Moreover, business oriented objectives, as customer satisfaction (through the latency) and the cost of using distributed FCs are also taken into account. The model introduced can be solved to optimality for instances with limited size. For larger instances, efficient solution methods should be proposed and tested. This aspect becomes crucial in view of possible extensions where the optimization of the FC tariffs is embedded into the model. This might be done by a combinatorial bi-level programming approach able to model the hierarchical decision-making process.

An interesting avenue for future research is the in-

corporation of green criteria, to assess the environmental impact of this paradigm compared to traditional non shared systems. In this respect, we hope that this paper will foster new researches to soon open the way of a large-scale implementation of this shared delivery system, where different FCs jointly provide services to drone delivery companies. This, in turn, could better satisfy the booming customers demand for on-time and fast delivery services.

REFERENCES

Aurambout, J.-P., Gkoumas, K., and Ciuffo, B. (2019). Last mile delivery by drones: an estimation of viable market potential and access to citizens across european cities. *European Transport Research Review*, 11(1):1–21.

Ben-Tal, A., Den Hertog, D., and Vial, J.-P. (2015). Deriving robust counterparts of nonlinear uncertain inequalities. *Mathematical programming*, 149(1):265–299.

Bruni, M. E., Khodaparasti, S., and Demeulemeester, E. (2020). The distributionally robust machine scheduling problem with job selection and sequence-dependent setup times. *Computers & Operations Research*, 123:105017.

Cheng, C., Adulyasak, Y., and Rousseau, L.-M. (2020). Drone routing with energy function: Formulation and exact algorithm. *Transportation Research Part B: Methodological*, 139:364–387.

Choi, Y. and Schonfeld, P. M. (2017). Optimization of multi-package drone deliveries considering battery capacity. In *Proceedings of the 96th Annual Meeting of the Transportation Research Board, Washington, DC, USA*, pages 8–12.

Dorling, K., Heinrichs, J., Messier, G. G., and Magierowski, S. (2016). Vehicle routing problems for drone delivery. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 47(1):70–85.

Duran, M. A. and Grossmann, I. E. (1986). An outer-approximation algorithm for a class of mixed-integer nonlinear programs. *Mathematical programming*, 36(3):307–339.

Kim, S., Kwak, J. H., Oh, B., Lee, D.-H., and Lee, D. (2021). An optimal routing algorithm for unmanned aerial vehicles. *Sensors*, 21(4):1219.

Kim, S. J., Lim, G. J., Cho, J., and Côté, M. J. (2017). Drone-aided healthcare services for patients with chronic diseases in rural areas. *Journal of Intelligent & Robotic Systems*, 88(1):163–180.

Liu, Y., Liu, Z., Shi, J., Wu, G., and Chen, C. (2019). Optimization of base location and patrol routes for unmanned aerial vehicles in border intelligence, surveillance, and reconnaissance. *Journal of Advanced Transportation*, 2019.

Nucamendi-Guillén, S., Angel-Bello, F., Martínez-Salazar, I., and Cordero-Franco, A. E. (2018). The cumulative capacitated vehicle routing problem: New formu-

lations and iterated greedy algorithms. *Expert Systems with Applications*, 113:315–327.

Nucamendi-Guillén, S., Martínez-Salazar, I., Angel-Bello, F., and Moreno-Vega, J. M. (2016). A mixed integer formulation and an efficient metaheuristic procedure for the k-travelling repairmen problem. *Journal of the Operational Research Society*, 67(8):1121–1134.

Torabbeigi, M., Lim, G. J., and Kim, S. J. (2020). Drone delivery scheduling optimization considering payload-induced battery consumption rates. *Journal of Intelligent & Robotic Systems*, 97(3):471–487.

Troudi, A., Addouche, S.-A., Dellagi, S., and Mhamedi, A. E. (2018). Sizing of the drone delivery fleet considering energy autonomy. *Sustainability*, 10(9):3344.