Urban Air Mobility: Multi-objective Mixed Integer Programming Model for Solving the Drone Scheduling Problem

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Abstract. In this paper the drone scheduling problem was considered. The mixed integer linear programming mathematical formulation for the considered problem based on minimizing total delays in servicing tasks and total flying time of all drones is proposed. The model takes into account tasks duration and significance. The mathematical formulation has been tested on the hypothetical examples. The generated mixed integer linear programs have been solved by CPLEX. The obtained results show that task assignments on fleet of drones depend on drone speed and the number of drones analyzed.

Keywords: Drones · UAM · scheduling · mixed integer programming · urban airspace

1 Introduction

Cohen et al. [1], in their paper about history, ecosystem, market potential, and challenges of Urban Air Mobility (UAM) define it as an emerging concept which envisions a safe, efficient, accessible, sustainable, affordable, and quiet air transportation system for (among other services) – goods/cargo delivery within or traversing metropolitan areas.

During the last few years, interest in the potential use of Unmanned Aerial Vehicles (UAV) for the delivery of small parcels has arisen due to their competitive advantages. Drones benefit the delivery of small parcels because they are: i) not restricted to established road networks, ii) do not require pilots, iii) are low cost, iv) do not require launching infrastructures, and v) in disease outbreaks, they can reduce the physical interaction between victims and rescue teams. Given the unique abilities of drones, the delivery of time-sensitive medical items to rural and suburban areas via drones can save time, cost, and, above all, people's lives [2].

Persson [3] in its work identifies "emerging drivers for drones' application in last-mile delivery, barriers for drones' application in last-mile delivery, and approaches for implementing drones in last-mile delivery". He also stated that drone routing problem on last-mile delivery is one of the currently most researched topics. Goal of solving this problem is to find the optimal delivery path at a minimum cost given a set of locations.

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Drones are seen here as a tool for a last-mile delivery from a truck with whom is working in tandem.

Borghetti et al. [4] studied usability of drones for last-mile delivery in Milan, Italy. For that purpose they performed a stated preference survey among end-users to assess their propensity towards drones. Based on findings they designed a delivery service by drones. Study shows that new service can be successfully used for small and light package deliveries, reducing in such a way environmental and social impacts, while ensuring profits delivery provider.

Drones are receiving popularity with time due to their advanced mobility. Although they were initially deployed for military purposes, they now have a wide array of applications in various public and private sectors. Drone scheduling is associated with optimization of drone flight routes and may include other features, such as determination of arrival time at each node, utilization of drones, battery capacity considerations, and battery recharging considerations.

Torabbeigi et al. [5] were trying to find a parcel delivery schedule using drones considering the battery consumption rate as a function of payload, using a mixed integer linear programming problem (MILP). The "least number of drones and their flight paths to deliver parcels while ensuring the safe return of the drones with respect to the battery charge level" were obtained as results. Similarly Bruni et al. [6] have proposed a metaheuristic "combining variable neighborhood descent with a cut generation approach" to resolve routing problem considering battery consumption rates.

Pachayappan and Sudhakar [7] are determining optimal pickup and delivery routes in drone operations minimizing the distance traveled to complete the scheduled deliveries and ensuring the optimal use of the battery capacity and safe return. They proposed a Mixed-Integer Linear Programming (MILP) model.

Moadab et al. [8] were studying a last-mile delivery problem in which a set of drones are operated in coordination with public transportation system used to enable drones to charge their batteries. For that purpose they proposed mathematical model based on Vehicle routing Problem which objective function was aiming to minimize the total energy that drones consumed in delivery operations.

Pasha et al. [9] conducts an extensive survey of the scientific literature that assessed drone scheduling problem They grouped the collected studies into different categories, including general drone scheduling, drone scheduling for delivery of goods, drone scheduling for monitoring, and drone scheduling with recharge considerations.

Ghelichi et al. [2] presents an optimization model to design the logistics for a fleet of drones for timely delivery of medical packages to remote locations. They present a time-slot formulation to model a location-scheduling problem to determine a set of trips for the available fleet of drones such that the total completion time of all trips is minimized. The proposed model aims to i) find optimal locations of charging stations, ii) schedule and sequence deliveries, and iii) determine a set of trips for each drone. They implemented a case study for Louisville, KY to provide in-depth managerial insights into costs and system performance metrics.

Deng et al. [10] were studying the problem of serving multiple customers with one drone flight considering energy consumption. For that, they have developed a multi-UAV task allocation model combined with vehicle path planning model. They proposed

a hybrid heuristic algorithm based on an improved K-means algorithm and ant colony optimization.

Li et al. [11] have considered parcel delivery in low-altitude urban airspace and proposed UAV traffic management system which includes path planning, conflict detection and resolution and airspace resource allocation.

Having in mind importance of the drone scheduling problem in the scientific community, in this paper a multi-objective mixed integer programming model for drone scheduling problem was proposed. The model was used to find optimal schedules for all drones within considered urban area.

Paper is organized in a following way. After Introduction section which presents a literature survey, in following section some drone operation and urban airspace constraints are presented followed by drone flight routing assumptions. Section III contains statement of the problem while Section IV detailed mathematical formulation of the drone scheduling problem. Numerical example was presented in Section V followed with brief analysis of results and some findings. Section VI presents some conclusions and direction for further research.

2 Drone Operation Constraints and Routing Assumptions

Routing (determining of the trajectory) for multiple drones in urban environments, where obstacles of different heights exist, become an important problem in drone operations. This problem is even more challenging in case of Beyond Visual Line of Site (BVLOS) operations. The objective of route design is to find suitable trajectories in 3D environment while ensuring collision-free navigation. The collision is prevented by three possible alternatives: i) forcing the drone to statically hover, so its peer can pass first, ii) making it fly at a different altitude, or iii) completely changing its path.

Multiple charging stations are made available to allow the drones to recharge their batteries when needed [12]. The proposed collision-free navigation solutions are proactive approaches determining the trip plan of each member of the fleet beforehand, i.e., before the motion of the fleet to ensure a safe flight for the drones [12]. Path (trajectory) planning (routing) is one of the fundamental problems that have to be solved.

2.1 Drone Operation Constrains

The following operation constraints are assumed in this study:

- Climb and descend are limited with 20 degrees off the horizon. For the purpose of calculation safe value of 15 degrees was used. With speed of 20m/s and angle of 15 degrees climb/descend speed of about 5.2 m/s is obtained.
- Drone in use is designed to keep constant air speed of 20m/s. Depending on the wind ground speed vary between 15–25 m/s (depending whether it is head or tail wind).
- Drone trajectory auto correction is conducted by two options
  - o drone is always trying to get to the next point, it means that if it's blown off the track it will maintain straight line to the next point,

p drone is following the line, then, if it's blown off the track, it will get on track back and then continue flight.

- Drone is not equipped with any visual obstacle avoidance system.
- Drone is keeping track in terms of height with deviation less than 10 m.
- Drone landing takes at least one minute.

2.2 Urban Airspace Constraints

The very low altitude urban airspace, where drones are expected to operate, contains operational complexities, due to the presence of obstacles as well as temporary and permanent no-fly-zones. This part of the airspace is also frequently occupied by general aviation aircraft and helicopters. Therefore, the urban airspace is heavily constrained. Nevertheless, many of these operational complexities (and their characteristics) are shared by ground-based traffic, for which there exists a wide body of literature [13].

Similar to road vehicles, drones can employ existing street networks and, thus, 'flyover-streets' in constrained urban spaces. However, with the expected large-scale drone traffic volumes, simply flying over streets may not be adequate to ensure airspace safety. When drones fly in competing travel directions in a constrained environment, a large number of conflicts would be triggered, due to high average relative velocities and limited flexibility of the airspace.

As a result, applying segmentation and alignment principles to this portion of the airspace, in particular, would organize traffic into different altitude layers with respect to travel directions and, thus, add more structure to the constrained environment [13].

2.3 Drone Flight Routing Assumptions

Considering urban airspace and drone operation constrains mentioned above, it was possible to define flight path that would be convenient for usage in this study. For illustration purposes a virtual city was used. In order to simplify solution as much as possible, it was assumed that data about city topography and obstacle heights, as well as geo location of city stations are known, e.g. three stations with corresponding coordinates (Station1: lat1, lon1; Station2: lat2, lon2; Station3: lat3, lon3 (Fig. 1)).

Figure 2 represents drone vertical flight path illustration at Virtual City. Station 1 is defined by latitude, longitude, elevation and object height. Station 2 is defined the same way. *Pt* is take-off point with same parameters as Station 1. *Pl* is landing point with same parameters as Station 2. *Pc* is defined by latitude, longitude and elevation and represents point where take-off and climb is finished and drone flight is transformed to cruise at certain height. *Pd* is point defined by latitude, longitude and elevation (same elevation as *Pc*) where descent for landing begins.

If *No flight area* is activated for the time drone has to fly from Station2 to Station3 (or vice versa), flight path is set to alternative path that avoids prohibited area (as shown on Fig. 3). Point *Pas* (Fig. 3) is starting point of alternative route. When drone reaches cruising height, it reroutes from direct route to alternative. *Pae* is point where alternative route ends and drone is pointed to destination.

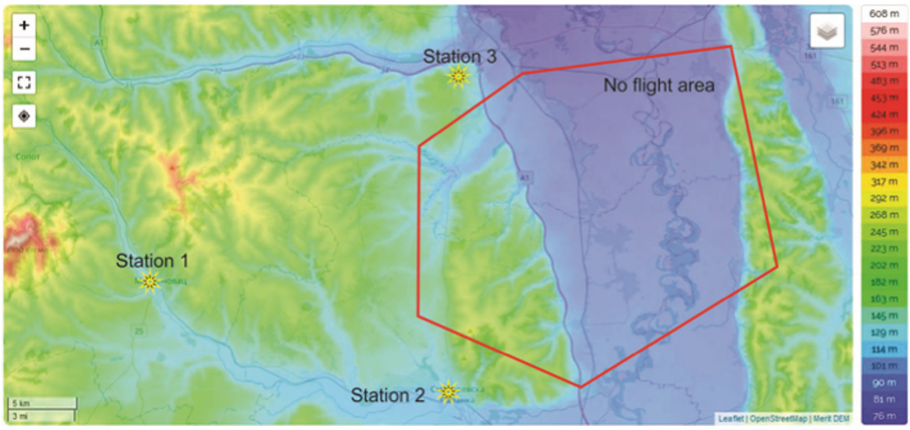

Fig. 1. Virtual city stations with corresponding geo location and elevation. Predefined No flight area is also represented.

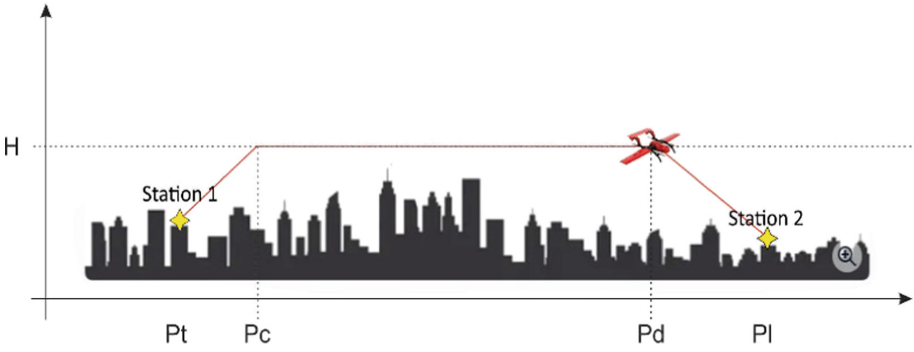

Fig. 2. Drone vertical flight profile illustration

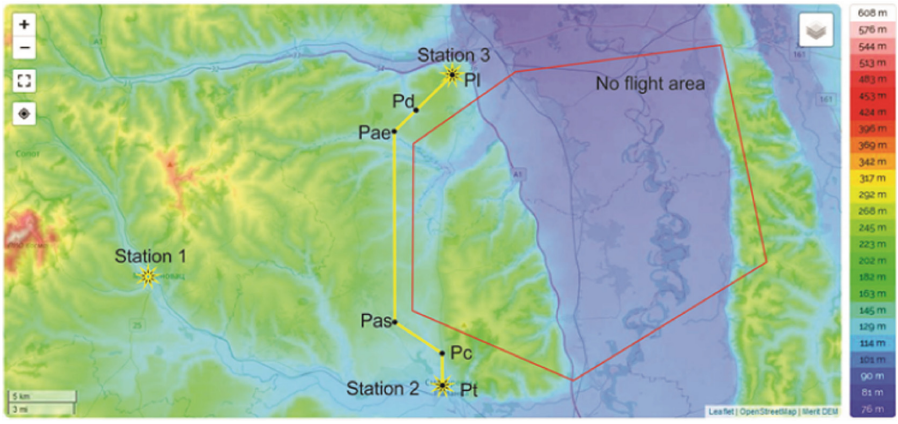

Fig. 3. Drone flight path Virtual City illustration with No flight area activated

3 Statement of the Problem

The problem of the assignment of the tasks to the available drones was considered in this study. It was supposed that there are n tasks, m drones and d drone stations. At the beginning, all drones are located at the same depot. Each task has the following characteristics: origin station (i, $i = 1,\ldots, d$), destination station ($j, j = 1,\ldots, d$), loading time at the station i and unloading time at the station j, the time when the service of the task should start and the coefficient that represents the significance of the task.

In the considered problem each task should be served by one drone. When the drone serves the last assigned task it has to return at the depot. All drones have the same characteristics.

The most important goal in this problem is to find the schedules of drones in the way to minimize the deviation from the required beginning of service of the tasks. The significance of the tasks should be also taken into consideration. The second goal is to minimize the drones' activities (for example, the total flying time of all drones).

Following modeling assumptions are used: each drone can carry only one parcel which payload is constant, battery consumption rate is not taken into account, delivery between fixed stations (e.g. hospitals) are considered (not last-mile delivery from trucks e.g.), operations are BVLOS, urban network contain finite number of fixed stations.

4 Mathematical Formulation for the Drone Scheduling Problem

The depot was denoted as node 0 and the tasks as nodes from 1 to n. Let explain in more detail how the task was represented as the node. Suppose that the drone, located at the depot, must serve two tasks and return to the depot. In the first task, the drone flies from station 1 to station 2, and in the second task, the drone flies from station 3 to station 4 (Fig. 4). It could be noticed that the drone will fly in the following way: depot – station 1 – station 2 – station 3 – station 4 – depot. This example can be also represented in the following way: the depot is node 0, the first task is node 1, and the second task is node 2. Now, the drone has the following route: 0 – 1 – 2 – 0 (Fig. 5). Comparing these two paths, one can notice that the travel time between nodes 0 and 1 is the same as the travel time between the depot and the origin station of task 1.

The travel time between nodes 1 and 2 is the travel time between the destination station of task 1 and the origin station of task 2.

A multi-objective mixed integer programming mathematical formulation for the considered problem was developed. The notations used in this formulation are given bellow.

Input data:

t_{ij} – travel time from the destination node of the task i to origin node of the task j,

tl_i – loading time of task i,

ts_i – service time of task i (travel time between the origin to destination station of task i),

tu_i – unloading time of task i,

r_j – time when the service of task j should start,

M – large positive number,

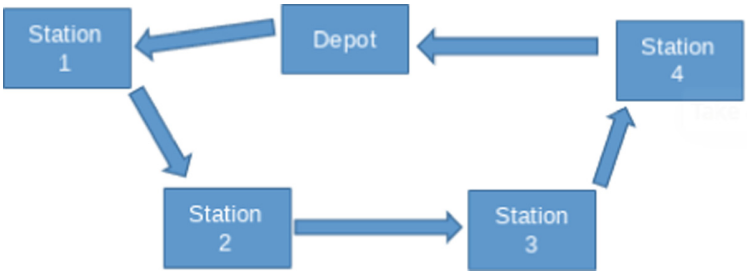

Fig. 4. The example of the drone route

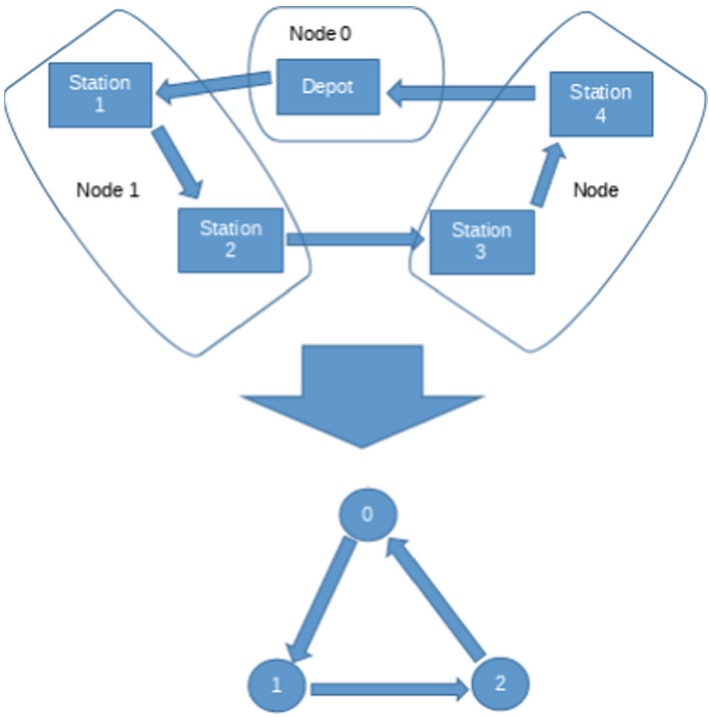

Fig. 5. The drone path when the depot and the tasks are given as the nodes

w_j – the coefficient of significance of the task j,
Decision variables:

$$x_{ijk} = \begin{cases} 1, & \textit{if the drone } k \textit{ after task } i \textit{ is going to serve task } j \\ 0, & \textit{otherwise} \end{cases}$$

s_{jk} – the time when the drone k starts to service of the task j,

y_{jk} – decision variable that represent delay from the required start of servicing of the task j by the drone k

The mixed integer programming model was developed to assign the tasks to the available drones. This mathematical formulation can be given in the following way:

$$\begin{aligned} &\text{Minimize} \\ &F_1 = \sum_{j=1}^{n} \sum_{k=1}^{m} w_j y_{jk} \end{aligned} \tag{1}$$

$$\begin{aligned} &\text{Minimize} \\ &F_2 = \sum_{i=0}^{n} \sum_{\substack{j=0 \\ i \neq j}}^{n} \sum_{k=1}^{m} t_{ij} x_{ijk} \end{aligned} \tag{2}$$

Subject to:

$$\sum_{\substack{i=0 \\ i \neq j}}^{n} \sum_{k=1}^{m} x_{ijk} = 1 \quad \forall j = 1, \cdots, n \tag{3}$$

$$\sum_{\substack{i=0 \\ i \neq j}}^{n} x_{ijk} - \sum_{\substack{i=0 \\ i \neq j}}^{n} x_{jik} = 0 \quad \forall j = 1, \cdots, n; k = 1, \cdots, m \tag{4}$$

$$\sum_{j=1}^{n} x_{0jk} \leq 1 \quad \forall k = 1, \cdots, m \tag{5}$$

$$\sum_{i=1}^{n} x_{i0k} \leq 1 \quad \forall k = 1, \cdots, m \tag{6}$$

$$s_{ik} + tl_i + ts_i + tu_i + t_{ij} - M \cdot \left(1 - x_{ijk}\right) \leq s_{jk} \quad \forall i = 1, \cdots, n; j = 1, \cdots, n;\ i \neq j;\ k = 1, \cdots, m \tag{7}$$

$$s_{jk} - y_{jk} = r_j \quad \forall j = 1, \cdots, n; k = 1, \cdots, m \tag{8}$$

$$x_{ijk} = \{0, 1\} \quad \forall i = 1, \cdots, n; j = 1, \cdots, n; i \neq j; k = 1, \cdots, m \tag{9}$$

$$s_{jk} \geq 0 \quad \forall j = 1, \cdots, n; k = 1, \cdots, m \tag{10}$$

$$y_{jk} \geq 0 \quad \forall j = 1, \cdots, n; k = 1, \cdots, m \tag{11}$$

Objective function (1) represents the total delay in servicing tasks. Objective function (2) calculates the total flying time of all drones. The both objective functions should be minimized.

Constraint (3) guarantees that all tasks will be served. Constraint (4) enables that the drone after finishing one task will go to another one or it will return to the depot. Constraint (5) defines that the drone can go from the depot to just one task. In the similar way constraint (6) guaranty that the drone have to return to the depot after finishing last assigned task. The time when the drone k will start to service the task j calculates according to the constraint (7). Delay of servicing of the tasks calculates by the constraint (8). Constraints (9), (10) and (11) define decision variables.

5 Numerical Example

In many cases of the considered problem the first objective function is significantly more important than the second one. Because of that, in this research, a lexicographic method of multi-objective optimizations has been applied.

According to this method, two mixed-integer programs have to be solved. In the first one, the first objective function and the set of constraints (3 - 11) have to be used.

After solving this program, the solution and the best value for the first objective function (let denote this value of the objective function with F_1^*) was obtained. The second mixed integer program consists of the second objective functions, the set of constraints (3–11), and one new constraint: $F_1 \leq F_1^*$. In that way, the solution was optimized in the way to minimize the second objective function, while the first objective function will not be worsened.

The lexicographic method has been applied to a small hypothetical example with five stations and ten tasks. For the stations the locations of the hospitals in the city of Belgrade (Republic of Serbia) are chosen. It was assumed that the depot is at the same location as the first station. Eight scenarios were analyzed depending on the speed of drones, the number of drones, and the tasks significance coefficients:

- Scenario 1: 3 drones with the average speed of 50 km/h for traveling and 10 m/s for taking off and landing and the same significance coefficients of the tasks,
- Scenario 2: 3 drones with the average speed of 50 km/h for traveling and 10 m/s for taking off and landing and different significance coefficients of the tasks,
- Scenario 3: 5 drones with the average speed of 50 km/h for traveling and 10 m/s for taking off and landing and the same significance coefficients of the tasks,
- Scenario 4: 5 drones with the average speed of 50 km/h for traveling and 10 m/s for taking off and landing and the different significance coefficients of the tasks,
- Scenario 5: 3 drones with the average speed of 30 km/h for traveling and 5 m/s for taking off and landing and the same significance coefficients of the tasks,
- Scenario 6: 3 drones with the average speed of 30 km/h for traveling and 5 m/s for taking off and landing and the different significance coefficients of the tasks,
- Scenario 7: 5 drones with the average speed of 30 km/h for traveling and 5 m/s for taking off and landing and the same significance coefficients of the tasks,
- Scenario 8: 5 drones with the average speed of 30 km/h for traveling and 5 m/s for taking off and landing and the different significance coefficients of the tasks.

Also, it was supposed that drones fly at the height of 100 m (Fig. 2). The total travel time (taking off time + travel time + landing time) in minutes between the stations for the first four scenarios are given in Table 1, and for the rest of them are given in Table 2. The characteristics of the tasks are given in Table 3 (duration) and Table 4 (significance).

All test examples were solved with CPLEX 20.1 software. The computer with the following performances was used: AMD Ryzen 7 3800 X with 32 GB of RAM memory, operating system: Ubuntu 21.10.

Table 1. The total travel time between the drone ports for the scenarios from 1 to 4

	Depot	St. 1	St. 2	St. 3	St. 4	St. 5
Depot	0	0	4.54	2.67	5.29	8.41
St. 1	0	0	4.54	2.67	5.29	8.41
St. 2	4.54	4.54	0	2.25	6.11	12.15
St. 3	2.67	2.67	2.25	0	5.66	10.28
St. 4	5.29	5.29	6.11	5.66	0	12.47
St. 5	8.41	8.41	12.15	10.28	12.47	0

Table 2. The total travel time between the drone ports for the scenarios from 5 and 8

	Depot	St. 1	St. 2	St. 3	St. 4	St. 5
Depot	0	0	7.68	4.56	8.93	14.13
St. 1	0	0	7.68	4.56	8.93	14.13
St. 2	7.68	7.68	0	3.87	10.29	20.35
St. 3	4.56	4.56	3.87	0	9.54	17.24
St. 4	8.93	8.93	10.29	9.54	0	20.90
St. 5	14.13	14.13	20.35	17.24	20.90	0

Table 3. The characteristics of the tasks – Duration

Task	Origin station	Destination station	Loading time [min]	Unloading time [min]
1	1	2	1	1
2	3	5	1	1
3	4	3	1	1
4	2	4	1	1
5	5	1	1	1
6	4	2	1	1
7	1	5	1	1
8	2	3	1	1
9	3	1	1	1
10	3	4	1	1

Table 4. The characteristics of the tasks - Significance

Task	Start of the service [min]	Significance	
		scenarios: 1, 3, 5, 7	scenarios: 2, 4, 6, 8
1	5	1	1
2	10	1	1.25
3	15	1	1.5
4	20	1	1.75
5	20	1	2
6	25	1	2.25
7	25	1	2.5
8	25	1	2.75
9	30	1	3
10	30	1	3.25

For each scenario, two mixed integer programs were solved, and the obtained results are given in Tables 5 and 6. Table 5 shows the obtained routes for each drone, and Table 6 shows the values of the objective functions as well as the required CPU times. The values for F_1, given in column 2 in Table 6, and the CPU time given in column 4 in Table 6, were obtained by solving the first mixed integer programs. The values for F_2 and the CPU times in column 5 in Table 6 were obtained by solving the second mixed integer programs.

It can be noticed that speed and the number of drones significantly influenced the quality of solutions. Comparing scenarios 1 and 3, 2 and 4, 5 and 7, 6 and 8, it can be seen that in all of these cases the solutions with a higher number of drones are significantly better. Similarly, comparing scenarios 1 and 5, 2 and 6, 3 and 7, 4 and 8, it can be concluded that faster drones significantly outperform the slower ones. Also, it can be noticed that the different significance of tasks mainly did not make a big difference between the routes.

It is very interesting to take into consideration the CPU time for solving considered examples. Generally, this is a small example and because of that, the CPU times are very small for all scenarios. Comparing the CPU times for solving mixed integer programs for three and five drones it can be concluded that examples with more drones can be solved faster. Also, the interesting fact is that solving the second mixed integer program (the second model) needs less time than the first one.

Table 5. The obtained solutions

Scenario	Drone	Route (assigned tasks)
1	1	0 - 2 - 5 - 10 - 0
	2	0 - 3 - 8 - 9 - 7 - 0
	3	0 - 1 - 4 - 6 - 0
2	1	0 - 1 - 4 - 6 - 0
	2	0 - 3 - 8 - 9 - 7 - 0
	3	0 - 2 - 5 - 10 - 0
3	1	0 - 1 - 8 - 10 - 0
	2	0 - 4 - 6 - 0
	3	0 - 2 - 5 - 0
	4	0 - 7 - 0
	5	0 - 3 - 9 - 0
4	1	0 - 1 - 4 - 6 - 0
	2	0 - 8 - 10 - 0
	3	0 - 7 - 0
	4	0 - 2 - 5 - 0
	5	0 - 3 - 9 - 0
5	1	0 - 1 - 4 - 6 - 10 - 0
	2	0 - 2 - 5 - 0
	3	0 - 3 - 8 - 9 - 7 - 0
6	1	0 - 1 - 8 - 9 - 7 - 0
	2	0 - 2 - 5 - 0
	3	0 - 3 - 10 - 6 - 0
7	1	0 - 1 - 8 - 9 - 0
	2	0 - 2 - 5 - 0
	3	0 - 7 - 0
	4	0 - 4 - 6 - 0
	5	0 - 3 - 10 - 0
8	1	0 - 8 - 9 - 0
	2	0 - 2 - 5 - 0
	3	0 - 3 - 10 - 0
	4	0 - 7 - 0
	5	0 - 1 - 4 - 6 - 0

Table 6. The solution characteristics

Scenario	Objective functions		CPU time [sec]	
	F_1	F_2	first model	second model
1	20.42	31.12	0.65	0.13
2	53.15	31.12	1.04	0.19
3	5.39	30.74	0.18	0.04
4	11.56	30.74	0.2	0.02
5	64.51	44.29	2.96	0.25
6	147.22	51.91	5.74	0.79
7	17.4	51.91	0.27	0.15
8	37.49	51.91	0.22	0.1

6 Conclusions

Proposed multi-objective mixed integer programming model for drone scheduling problem solved by CPLEX have provided in fast manner a route (assigned tasks) per each drone.

The obtained results show that task assignments on fleet of drones depend on drone speed and the number of drones analyzed.

Future research are planned to go in two directions. One is relaxation of certain assumptions, such as e.g. inclusion of battery consumption in a criteria or use of different payload parcels, increase of network of stations and integration of model into digital map of the city.

Other research direction is related to testing examples with more stations and tasks. Most probably, the solution approach proposed in this report will cause much bigger values of the CPU time. In that case, it should be developed some heuristic or metaheuristic algorithms for the considered problem.

Limitation for selection of optimal drone route in this study is that drones do not have any sensors (cameras, radar, lidar, etc.) that can influence route optimization.

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