Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 52-13 (2019) 820–825

# Planning deliveries with UAV routing under weather forecast and energy consumption constraints

**Amila Thibbotuwawa,* Grzegorz Bocewicz,** Peter Nielsen,* and Banaszak Zbigniew****

* *Dept. of Materials and Production, Aalborg University, Aalborg, Denmark (e-mail;peter@mp.aau.dk, amila@mp.aau.dk)*

** *Dept. of Computer Science and Management, Koszalin University of Technology, Poland, bocewicz@ie.tu.koszalin.pl, Zbigniew.Banaszak@tu.koszalin.pl*

Abstract: In this paper, a depth-first search strategy to cope with the problem of multi-trip unmanned aerial vehicle (UAV) fleet mission planning is proposed. The considered UAVs delivery problem aims at a trajectory planning issue addressed for UAVs operating in a hostile environment while considering battery and payload weight as well as vehicles reuse. Employed UAVs fly on a 3D plane matching a distribution network while servicing customers and ensuring collision avoidance among team members. The objective is to get a sequence of submissions that ensures delivery to customers satisfying the requested amount and demands within a given time horizon. The method proposed in this paper offers solutions to several questions related to the multistage mission planning that could be applied to solve problems such as minimizing energy consumption, conducting the mission in the shortest possible time, just-in-time replenishing of supplies, and so on. The computational experiment illustrates possibilities of the proposed method.



*Keywords:* UAV routing and scheduling; UAV fleet mission planning, weather forecast and energy consumption constraints, delivery service.

## 1. INTRODUCTION

The problems of goods delivery mission planning for UAV fleets are the subject of intensive research (AbdAllah et al. 2017; Bekhti et al. 2017; Thibbotuwawa et al. 2019). Their roots go back to the well-known extensions of the vehicle routing problem (VRP) addressing the routing and scheduling of UAVs to deliver goods from a depot to customer locations. Rising expectations following the new outdoor applications force one to consider other aspects such as the weather forecast and energy consumption. Typical limitations on the implementation of UAVs in transportation systems include the limited distance (dependent on the battery capacity—Nguyen et al. 2017, weather conditions), overlapping air corridors designated for UAV movement (leading to collisions and deadlocks) as well as selected technical parameters (e.g., speed, maximum payload) (Bocewicz et al. 2019).

The objective is to get a sequence of submissions that ensures delivery to customers satisfying the requested amount and demands within a given time horizon (Ham 2018). In that context, the present research addresses the problems of routing and scheduling of a UAV fleet, taking into account the changing weather conditions (wind speed and direction). The study's focus is on solutions that allow finding admissible (collision-free - Geyer et al. 2008, non-empty battery - Thibbotuwawa et al. 2019) plan of delivery submissions, that is, composed of a sequence of UAV multi-trip-like flights which guarantee the satisfaction of all given customers' orders.

Therefore, the considered reference model of UAVs driven distribution system takes into account data specifying weather forecast (including wind direction and speed), number of customers and depots, customers' demand, fleet size (composed of homogenous vehicles), parameters describing UAV (such as payload, energy limit, width, and so on), flight distances among customers and depots, time horizon and so on. Following a given weather forecast, the time horizon can be subdivided into so-called weather time windows (assuming the same wind speed and direction), which in turn can be arbitrarily subdivided into so-called flying time windows (i.e., periods during which a UAV of a given energy limit can fly). The number of flying time windows (FTW) generate the number of stages of the overall (i.e., final) delivery mission. At each stage, a set of admissible (i.e., collision-free) submissions are created, that is, the submissions that might be potentially included in a sequence of finally planned UAVs fleet delivery mission. Treating such a set of subsets of admissible submissions as a state space (composed of a set of subsets), a depth-first search strategy is employed to arrive at a final plan of the delivery mission, that is, an admissible sequence of submissions, guaranteeing 100% fulfillment of the customers' delivery.

Computer implementation of the above-mentioned framework (including the reference model and a depth-first search strategy) enables the consideration of a decision-support tool for multiple UAV mission routing and able to assess mixed-fleet policies employed in the course of delivery mission planning. Such a DSS (employed commercially available solvers CPLEX and/or Gurobi) aimed at planning deliveries with UAV routing plays a crucial role in the assessment of a variety of delivery scenarios. From this perspective, expected results will fall within the scope of research, reported in previous papers ( Bocewicz et al., 2019), ( Bocewicz et al., 2018), and (Thibbotuwawa et al., 2019).

The remainder of the paper is structured as follows. Section 2 provides an overview of literature. A reference model of a

2405-8963 © 2019, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2019.11.231

UAV fleet routing and scheduling problem is discussed in Section 3. Section 4 presents the methods aimed at UAVs delivery missions planning. An illustrative example of the approach used is delivered in Section 5. Conclusions are formulated and the main directions of future research are suggested in Section 6.

## 2. LITERATURE REVIEW

UAV mission planning treated as an extension of VRP (Dorling et al., 2016) belongs to the class of planning problems (AbdAllah, Essam and Sarker, 2017) which have different degrees of attractiveness when evaluated against multiple decision criteria. Influencing parameters for decision criteria in UAV mission planning include numerous parameters and constraints. It can be seen that the decision space comprises the following aspects: routing and scheduling in a 3D environment, changing weather conditions (e.g., wind speed, wind direction, air density), UAVs technical parameters, energy consumption affected by weather conditions, carrying payload, collision avoidance with respect to moving (e.g., UAVs) and fixed objects. All these elements emphasize the intractability of mission planning as it is challenging to develop models considering all the influencing aspects together.

Existing methods for UAV flight planning have focused predominantly on finding paths that satisfy vehicle dynamics, assuming linear fuel consumption, while avoiding fixed obstacles (Yang and Kapila, 2002). In general, researchers have used methods such as deterministic, heuristic-based algorithms and probabilistic, randomized algorithms (Bekhti et al., 2017). In this study, we propose a deterministic approach. Existing approaches fall into the categories of online mission planning and offline mission planning. In online mission planning, studies have assumed that the UAVs can detect the obstacles to avoid collisions.

The approaches to avoiding collisions differ when the fleet of UAVs is flying in free space vs dedicated corridors. In online mission planning regarding moving obstacles, collision avoidance is done through detection by sensors (Geyer, Singh, and Chamberlain, 2008) and by using collision avoidance constraints. In the context of free space, existing research has avoided collisions through detection sensors (Geyer et al 2008), and in the case of dedicated corridors, missions are organized by satisfying collision avoidance constraints. In offline mission planning, collision avoidance is done through predicting strategies where planning the missions are done avoiding the collisions with respect to fixed obstacles (Su et al. 2009; Wang et al. 2015). This study focuses on offline mission planning of UAVs where the collisions are predicted and missions are planned to ensure collision avoidance by satisfying the collisions avoidance constraints.

UAVs are limited by loading capacity as well as flight duration which is related to the energy capacity, and these characteristics should be taken into consideration in mission planning (Song and Kim, 2018). Certain studies has proposed to divide the whole area taking into account UAVs' relative capabilities (Maza and Ollero, 2007) and proposed to cluster the area to reduce the problem size (Xu *et al.*, 2001; Wang *et al.*, 2015). In this study, customer nodes are clustered for each flying time window, and for each cluster, a set of feasible UAVs fleet routings and accompanying schedules are calculated taking into account the weather conditions imposing the energy consumption constraints. Seldom research has focused on considering wind condition on energy consumption and simultaneously using that information in planning the missions (Rubio and Kragelund, 2003; Dorling *et al.*, 2016). Certain studies have assumed constant wind speed and direction (Rubio and Kragelund, 2003) and have used linear approximations for energy consumption ,and have not considered the impact of weather (Dorling et al., 2016). However, for the UAVs used in this study, linear approximations are not reasonable as the weight of the UAVs are larger than the UAVs used in existing research (in existing research considered weight of UAVs are less than 4 Kgs (Dorling et al., 2016), whereas in this study the considered weight is more than 40 Kgs). Such studies have stated that their models are not reasonable when the weight of UAVs increases.

Existing research does not adequately accompany all the requirements for UAV mission planning considering organizing delivery networks to deliver customer demands during a time horizon with changing weather with the goal of fulfilling all customer demands before the end of time horizon.

## 3. MODELING

The mathematical formulation of the model considered employs the following:

### *3.1 Parameters*

**Network**

$G = (N, E)$ Graph representing transportation network: $N = \{0 \dots n\}$ is a set of nodes and $E = \{\{i, j\} | \, i, j \in N, i \neq j\}$ is a set of edges

$CL_{m,l} = (N_{m,l}, E_{m,l})$ Subgraph of $G$ representing m[th] cluster in $l^{th}$ flying time time window: $N_{m,l} \subseteq N$ and $E_{m,l} \subseteq E$

$D_i$ Demand at node $i \in N$, $i \neq 0$

$d_{i,j}$ Travel distance from node $i$ to $j$

$t_{i,j}$ Travel time from node $i$ to $j$

$b_{\{i,j\};\{\alpha,\beta\}}$ Binary variable of blocking edges.

$$b_{\{i,j\};\{\alpha,\beta\}} = \begin{cases} 1 & \text{when an edge } \{i,j\} \text{ and } \{\alpha,\beta\} \text{ is utilized} \\ 0 & \text{otherwise.} \end{cases}$$

**UAV Technical Parameters**

$K$ Size of the fleet of UAVs

$Q$ Maximum loading capacity of a UAV

$vg_{i,j}$ Ground speed of a UAV from node i to j

$va_{i,j}^{l}$ Airspeed of a UAV from node i to j in $l^{th}$ flying time window, $va_{i,j}^{l} = \left[\overline{va_{i,j}^{l}}, \underline{va_{i,j}^{l}}\right]$ where: $\overline{va_{i,j}^{l}} / \underline{va_{i,j}^{l}}$ is minimum/maximum range of $va_{i,j}^{l}$

$P_{max}$ Maximum energy capacity of a UAV

**Environmental Parameters**

$H$ time horizon $H = [0, t_{max}]$

$W_T$ weather time window $T$: $W_T = [WS_T, WE_T]$, $WS_T$ / $WE_T$ is a start/end time of $W_T$

$F_l$ flying time window $l$: $F_l = [FS_l, FE_l]$, $FS_l/FE_l$ is a start time of $F_l$

$vw_l$ Wind speed in $l^{th}$ flying time window: $vw_l = \left[\overline{vw_l}, \underline{vw_l}\right]$ where: $\overline{vw_l} / \underline{vw_l}$ is minimum/maximum range of $vw_l$

### 3.2 Decision Variables

$x_{i,j}^{k}$ binary variable used to indicate if $k^{\text{th}}$ UAV travels from node i to node j

$x_{i,j}^{k} = \begin{cases} 1 & \text{if } k^{\text{th}} \text{ UAV travels along from node i to node j} \\ 0 & \text{otherwise.} \end{cases}$

$y_i^k$ Time that $k^{\text{th}}$ UAV arrives at the node $i$

$c_i^k$ Payload weight amount delivered to node $i$ by $k^{\text{th}}$ UAV

$f_{i,j}^{k}$ Payload weight carried by a UAV from node i to j by $k^{\text{th}}$ UAV

$S_{n,m,l}$ $n^{th}$ submission in $m^{\text{th}}$ cluster in $l^{\text{th}}$ flying time window

$RL_{n,m,l}$ $n^{th}$ scenario in $m^{\text{th}}$ cluster in $l^{\text{th}}$ flying time window: $RL_{n,m,l} = (R_{n,m,l}, P_{n,m,l}, CS_{n,m,l})$ where: $R_{n,m,l}$ is a route of scenario, $P_{n,m,l}$ schedule of scenario, $CS_{n,m,l}$ customer satisfaction levels of scenario

### 3.3 Constraints

**Arrival time at nodes**

Relationship between the binary decision variable of $x_{i,j}^{k}$ and the decision variable of $y_i^k$.

$$(x_{i,j}^{k} = 1) \Rightarrow (\, y_j^k = y_i^k + t_{i,j} + w) \quad \forall (i,j) \in N, \forall k \in K \quad (1)$$

where: $w$ - time spent for take-off and landing of a UAV

If a UAV $k$ is flying from node i to j, then arrival time $y_j^k$ to node $j$ is equal to the sum of travel time $t_{i,j}$ between node $i$ to $j$, time spent for take up landing $w$ and the arrival time $y_i^k$ to node $i$ (1).

**Collision avoidance**

This corresponds to the blocking edges, which are utilized by UAV $k$ and UAV $v$. The blocking edges ($b_{\{i,j\};\{\alpha,\beta\}} = 1$) should not be used in the same time when they are occupied by the UAVs ($x_{i,j}^{k} = 1$ and $x_{\alpha,\beta}^{v} = 1$).:

$$(b_{\{i,j\};\{\alpha,\beta\}} = 1) \wedge [(x_{i,j}^{k} = 1) \vee (x_{j,i}^{k} = 1)] \wedge \; [(x_{\alpha,\beta}^{v} = 1) \vee (x_{\beta,\alpha}^{v} = 1)]$$
$$\Rightarrow [(y_j^k \le y_\alpha^v) \vee (y_j^k \le y_\beta^v) \vee (y_i^k \le y_\beta^v) \vee (y_i^k \le y_\alpha^v)]$$
$$k = 1 \ldots K,\ v = 1 \ldots K,\ k \neq v, \{i,j\}, \{\alpha,\beta\} \in E \quad (2)$$

**Capacity**

The demand assigned to a UAV should not exceed its capacity.

$$\textstyle\sum_{i\in N_{m,l}} \sum_{j\in N_{m,l}} x_{i,j}^{k} c_j^k \leqslant Q \quad k = 1 \ldots K \quad (3)$$

Sum of all the carried weights $c_j^k$ by UAV $k$ should not exceed the maximum carrying payload $Q$.

**Flow of UAVs**

When a UAV arrives at a node, that UAV must leave from that node.

$$\sum_{j\in N_{m,l}} x_{i,j}^{k} - \sum_{j\in N_{m,l}} x_{j,i}^{k} = 0, \quad k = 1 \ldots K,$$
$$\forall i \in N_0 = N_{m,l} \cup \{0\} \quad (4)$$

Sum of all the occupied edges which go to node $i$ ($\sum_{j\in N_{m,l}} x_{j,i}^{k}$) should be equal to the sum of all the edges, which leave from node $i$ ($\sum_{j\in N_{m,l}} x_{i,j}^{k}$).

**Start and end of routes**

Each UAV that departs from the depot (Node 0) should come back to the depot.

$$(x_{i,j}^{k} > 0) \Rightarrow (\textstyle\sum_{i\in N_{m,l}} x_{0,i}^{k} = \sum_{i\in N_{m,l}} x_{i,0}^{k} = 1\ )\ 1 \ldots K \quad (5)$$

Constraint (5) makes sure that each UAV departs from the depot (Node 0) and comes back to the depot. The sum of all the edges that start from node 0 and the sum of all the edges that return to node zero should be equal to one.

**Energy**

UAV has a maximum energy capacity of $P_{max}$, and in flight, it is not possible to consume energy which is higher than $P_{max}$.

$$\textstyle\sum_{i\in N_{m,l}} \sum_{j\in N_{m,l}} x_{i,j}^{k} P_{i,j}^{k} t_{i,j} \leqslant P_{max} \qquad k = 1 \ldots K \quad (6)$$

Explains that energy consumed by the $k^{\text{th}}$ UAV should be less than or equal to the maximum energy capacity of the UAV.

$$P_{i,j}^{k} = \frac{1}{2} C_D A D (va_{i,j}^{l})^3 + \frac{\left(ep + f_{i,j}^{k}\right)^2}{D b^2 va_{i,j}^{l}} \quad (7)$$

where $C_D$ is the aerodynamic drag coefficient, $A$ is the front facing area, $ep$ is the empty weight of the UAV, $D$ is the density of the air, and $b$ is the width of the UAV. The airspeed of a UAV $va_{i,j}^{l}$ is defined in the following way:

$$va_{i,j}^{l} = \sqrt{\left(vg_{i,j}\cos\vartheta_{i,j} - vw_l\cos\theta_l\right)^2 + \left(vg_{i,j}\sin\vartheta_{i,j} - vw_l\sin\theta_l\right)^2} \quad (8)$$

where: $\vartheta_{i,j}$ - angle of the vector of ground speed $vg_{i,j}$; $\theta_l$ - wind direction in $l^{\text{th}}$ flying time window

### 3.4 Assumptions

Basic principles of this study concerns a weather forecast which should be known in advance with sufficient accuracy to specific so-called weather time windows (WTW), in which constant weather conditions exist, such as speed and direction of the wind. WTWs following from a given weather forecast can be subdivided into flying time windows (FTW), treated as a size of the time used in the flying of a UAV considering the maximum energy limit and maximum carrying payload. Following the above, we assume that every traveled route of a UAV starts and finishes within a given flying time window and an amount of weight allocated to the customers in a route is an integer. Moreover, it is assumed the all UAVs in the fleet are homogeneous and are equipped with full energy capacity before the start of FTW, as well as being able to deliver the same kind of material. Each UAV has enough energy capacity to travel directly to the farthest customer in the network and come back directly to the depot in worst acceptable weather conditions. Also, more than one UAV can start to fly from the base in the same time. Deliveries being accepted by customers at any time during the time horizon are supplied through the given network of flying corridors.

### 3.5 Problem statement

The considered problem assumes that a given set of customers at different points is to be served during a time horizon, which consists of changing weather conditions, by a fleet of UAVs charged from a charging depot. The goal is to fulfill all the customer demands, such that each customer is reached with the required demand before the end of the time horizon while obeying the energy constraints and collision avoidance of UAVs. Given are:

- *Environmental parameters:* $H, W_T, F_l, vw_l$
- *Network parameters:* $G, D_i, d_{i,j}, t_{i,j}, b_{\{i,j\};\{\alpha,\beta\}}$
- *UAV Technical Parameters:* $K, Q, vg_{i,j}, va_{i,j}^{l}, P_{max}$

A main problem boils down to the question: *Does there exist a set of admissible missions (determined by decision variables: $S_{n,m,l}$, $RL_{n,m,l}$, $x_{ij}^{k}$, $y_i^k$, $c_i^k$, $f_{i,j}^{k}$ ) of given UAVs' fleet which guarantee that all the customer demands ($D_i$) will be satisfied* *under weather conditions considering energy constraints (6), collision avoidance (2), and constraints (3)-(5)?*

The above problem can be decomposed into five subproblems.

**I.** *How many weather time windows should be extracted in the horizon H? What are the values of variables determining the weather time windows $W_T$?*

**II.** *How many flying windows should be extracted in each weather time window? What are the values of variables determining the flying time windows: $F_l$, $vw_l = [\overline{vw_l}, \underline{vw_l}]$, $\theta_l$?*

**III.** *How many clusters $CL_{m,l} = (N_{m,l}, E_{m,l})$ should be extracted from the transportation network in each flying time window?*

**IV.** *Does there exist the set $S_{m,l} = \{S_{1,m,l}, \ldots, S_{q,m,l}\}$ of admissible submissions satisfying the energy constraints and collision avoidance of UAVs?*

**V.** *Does there exist the set of admissible submissions guaranteeing all customers demand fulfillment, such that the sum of the submission deliveries provides all customers demand fulfillment?*

## 4. METHOD

**Solution to subproblem I**

Using the actual historical weather data , the possible length of weather time windows are determined by analyzing the historical weather data and finding similar patterns in historical data for the given time horizon.

**Solution to subproblem II.**

Based on the traveling time of the UAV (considering the maximum energy limit and maximum carrying payload) flying time windows are determined by using the specifications of the UAV and the energy calculation formula.

**Solution to subproblem III.**

Customer clusters are made arbitrarily in by determining the number of customers to be put in the cluster. Determining the number of customers to be put in the cluster can be done in several ways, and one such way is to choose a number randomly between 2 and the maximum number of customers in the network.

**Solution to the subproblem IV.**

As the UAV needs to maintain a constant ground speed, it needs to adjust its airspeed to fly in the desired flight path. Each WTW consists of a min and max range of wind speed and a specific wind direction. This leads to a min and max range of airspeed due to the effect of the wind speed and direction. Using the min and max range of airspeed, the range of energy consumption is calculated.

The method to create a possible set of submissions (determined by routes and schedules guaranteeing services performed by fleet's UAV) for a cluster in a given FTW has two stages.

- Stage one: Create a list of scenarios for the cluster,
- Stage two: Create submissions ensuring collision avoidance using the scenarios made in stage one.

**Solution to the subproblem V**.

All sets of possible sequences of submissions are searched to find admissible missions by inserting all the possible sequences of submissions and searching all the sequences to find admissible sequences.

Finally, the solutions to the above-mentioned subproblems are employed in the methodology composed of the following stages:

- a given weather forecast covering the assumed time horizon is subdivided into WTWs (assuming the same wind speed and direction), which in turn are arbitrarily subdivided into FTWs (see subproblems I and II),
- for each FTW, a set of arbitrarily selected clusters of customers is assigned, and then for each cluster an arbitrarily assumed number of admissible (i.e., collision-free) submissions are created (see subproblems III and IV),
- treating the set of subsets of admissible (i.e., collision-free and guaranteeing 100% fulfillment of customers delivery) submissions as a state space, a depth-first search strategy is employed to get a final plan of delivery mission, that is, a sequence composed of submissions the number of which is equal to the number of FTWs distinguished by submissions (see subproblem V).

## 5. COMPUTATIONAL EXPERIMENTS

Experiments were run with historical data. All experiments were performed with a fleet of UAVs having the characteristics mentioned in section 3. Description of the input data used for the experiments are shown in Fig. 2. By using the input data, submissions are created for each cluster for each flying time window. After generating the possible submissions, the submissions which give higher customer satisfactions are selected for each flying time window and are presented in Fig.3. From the submissions created for each cluster in each flying time window, the best admissible sequence of submissions are presented which guarantee all customer demands in Fig.3. The objective of the study is to find an admissible sequence of submissions where all the customer demands are satisfied by the end of the time horizon. As a secondary objective, solutions that minimize total delivery time can be searched if several admissible solutions exist.

There are different submissions with the same fleet size but with a different number of customers per route which delivers the same demand quantities to the customers (example: *K*= 3, *Cn*=2 and *K*= 3, *Cn*=1). Submissions that consists of the same fleet size with a lower number of customers per route can be executed in shorter flying time windows and results in less total distance traveled in contrast to the submissions, which consists of the same fleet with a higher number of customers per route. (Example: *K* = 3, *Cn* =1, distance = 52.8 Km, length of flying time window =30 min and *K* = 3, *Cn* =2, distance = 82.8 Km, length of flying time window = 40 mins). This relationship can be used as a rule in creating submissions and should be tested for larger size instances to verify in future research. All experiments were conducted on a personal computer with 2.7 GHz speed and 8 Gb RAM. The calculation corresponding to the presented results corresponds to 2.3 min computation time which is fast enough for off-line planning.

## 6. CONCLUSIONS

The main contribution of this paper is presenting a depth-first search strategy to solve the problem of the multi-trip of a UAV fleet mission planning in changing weather conditions.

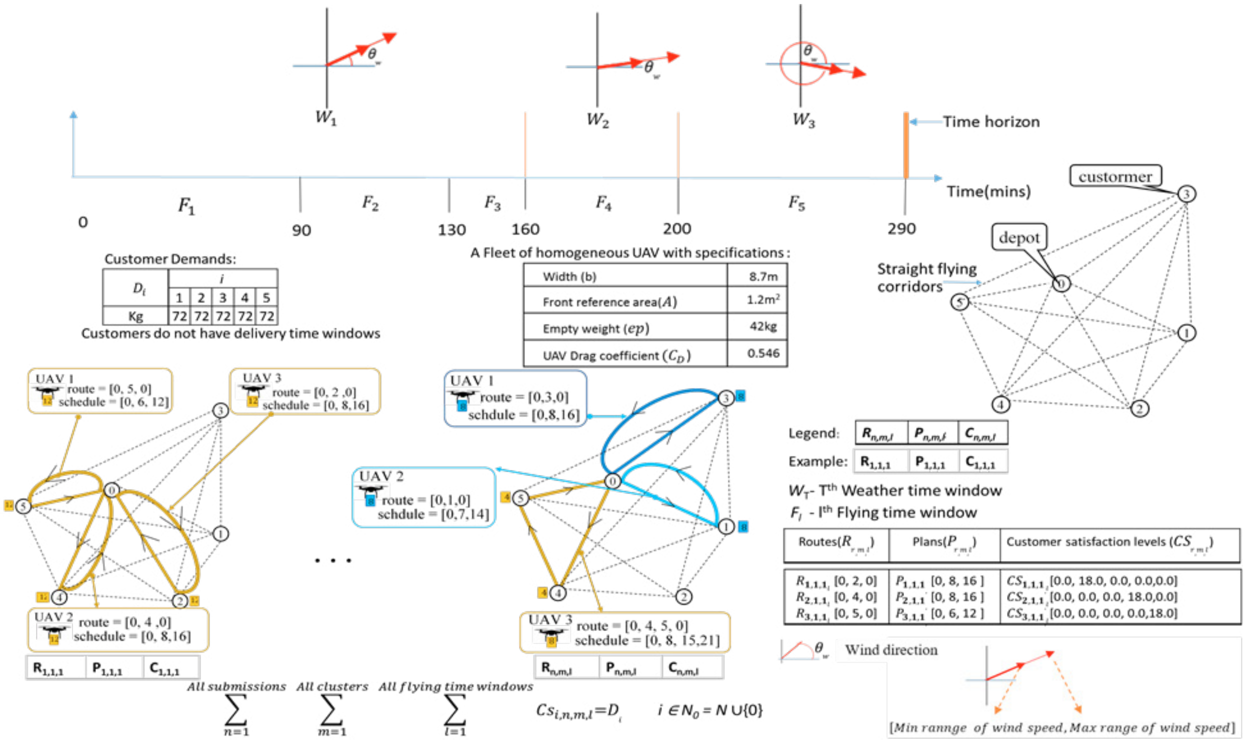


Fig 1 Graphical abstract illustrating problem modelling

| Input Data | Values |
|---|---|
| Maximum energy of UAV | [6000,12000] (KJ) |
| UAV fleet size | [2,3] |
| Number of flying time windows | 5 |
| Number of clusters per flying time window | 2 |
| Number of scenarios per cluster | 3 |
| Number of submissions per cluster | 2 |
| Number of customers per route | [1,2,3] |
| Distances between nodes | $d_{i,j}$ (km) |
| Ground speed | 20 (m/s) |
| Length of flying time window | [90,40,30,40,90](mins) |
| Maximum loading capacity of UAV | [12,24] (Kg) |

| Weather time window | 1 | 1 | 1 | 2 | 3 |
|---|---|---|---|---|---|
| Flying time window | 1 | 2 | 3 | 4 | 5 |
| Min wind speed(m/s) | 9 | 9 | 9 | 8 | 8 |
| Max wind speed(m/s) | 12 | 12 | 12 | 11 | 12 |
| Wind direction (degrees) | 30 | 30 | 30 | 10 | 330 |

Distance data between nodes in km

| $d_{i,j}$ | | j | | | | | |
|---|---|---|---|---|---|---|---|
| | | 0 | 1 | 2 | 3 | 4 | 5 |
| i | 0 | 0 | 7.2 | 8.4 | 8.4 | 8.4 | 6 |
| | 1 | 7.2 | 0 | 6 | 4.8 | 6 | 9.6 |
| | 2 | 8.4 | 6 | 0 | 9.6 | 8.4 | 8.4 |
| | 3 | 8.4 | 4.8 | 9.6 | 0 | 9.6 | 8.4 |
| | 4 | 8.4 | 6 | 8.4 | 9.6 | 0 | 7.2 |
| | 5 | 6 | 9.6 | 8.4 | 8.4 | 7.2 | 0 |

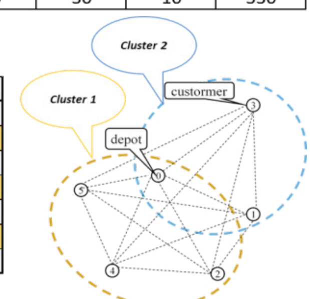


Fig. 2. Illustration of input data for the experiments

This paper provides an off-line solution approach for the problem of UAVs mission planning considering energy consumption constraints and collision avoidance of UAVs. A predictive strategy is used to avoid the collisions between UAVs where collision-free routings and schedules are created to service the customers during the time horizon. The proposed solution approach is tested using historical data and the results are presented. For WTWs with more than 13 m/s wind speeds, submissions, which contains routes, which have more than two customers per route, are not possible by the UAVs with maximum energy limits of 6,000 KJ. Thus depending on the weather forecast, the fleet size, and the number of customers per route can be decided in creating submissions. Submissions with a higher fleet size require a higher length of flying time windows as the fleet size increases the number of possible collisions increases.

In the current study, a single depot is considered, and multiple depots with recharging stations could be studied as a method of extending the flight distance of UAVs. Moreover, the method can be extended for reusability of UAVs inside the FTWs. In further research, it would be useful to compare the effectiveness and usability of proposed model with alternative models and the study can be extended with secondary objectives in minimizing energy consumption with regard to sustainability concerns.

## REFERENCES

AbdAllah, A. M. F. M., Essam, D. L. and Sarker, R. A. (2017) 'On solving periodic re-optimization dynamic vehicle routing problems', Applied Soft Computing Journal. Elsevier B.V., 55, pp. 1–12.

Bekhti, M., Achir, N., Boussetta, K. and Abdennebi, M. (2017) 'on Internet of Things EAI Endorsed Transactions Drone Package Delivery : A Heuristic approach for UAVs path planning and tracking', 3(9), pp. 1–11.

Best solutions for first 5 flying time windows for cluster 1

Weather time window 1, Flying time window 1

| | K | Q | Cn | $P_{max}$ | Customer received quantity(Kg) | Distance |
|---|---|---|---|---|---|---|
| 1 | 2 | 12 | 3 | 6000 | [0.0, 8.0, 0.0, 8.0, 8.0] | 60 |
| 2 | 2 | 12 | 3 | 12000 | [0.0, 8.0, 0.0, 8.0, 8.0] | 56.4 |
| 3 | 2 | 24 | 3 | 6000 | [0.0, 16.0, 0.0, 16.0, 16.0] | 56.4 |
| 4 | 3 | 24 | 2 | 12000 | [0.0, 24.0, 0.0, 24.0, 24.0] | 79.2 |
| 5 | 3 | 12 | 1 | 6000 | [0.0, 12.0, 0.0, 12.0, 12.0] | 52.8 |

Weather time window 1, Flying time window 2

| | K | Q | Cn | $P_{max}$ | Customer received quantity(Kg) | Distance |
|---|---|---|---|---|---|---|
| 1 | 2 | 12 | 3 | 12000 | [0.0, 8.0, 0.0, 8.0, 8.0] | 56.4 |
| 2 | 2 | 24 | 3 | 6000 | [0.0, 16.0, 0.0, 16.0, 16.0] | 60 |
| 3 | 2 | 24 | 3 | 12000 | [0.0, 16.0, 0.0, 16.0, 16.0] | 56.4 |
| 4 | 3 | 12 | 2 | 12000 | [0.0, 12.0, 0.0, 12.0, 12.0] | 79.2 |
| 5 | 3 | 24 | 2 | 6000 | [0.0, 24.0, 0.0, 24.0, 24.0] | 79.2 |

Weather time window 1, Flying time window 3

| | K | Q | Cn | $P_{max}$ | Customer received quantity(Kg) | Distance |
|---|---|---|---|---|---|---|
| 1 | 3 | 12 | 1 | 6000 | [0.0, 12.0, 0.0, 12.0, 12.0] | 52.4 |
| 2 | 3 | 24 | 1 | 6000 | [0.0, 24.0, 0.0, 24.0, 24.0] | 52.4 |
| 3 | 3 | 12 | 1 | 12000 | [0.0, 12.0, 0.0, 12.0, 12.0] | 52.4 |
| 4 | 3 | 24 | 1 | 12000 | [0.0, 24.0, 0.0, 24.0, 24.0] | 52.4 |
| 5 | 2 | 12 | 2 | 6000 | [0.0, 6.0, 0.0, 12.0, 6.0] | 57.6 |

Weather time window 2, Flying time window 3

| | K | Q | Cn | $P_{max}$ | Customer received quantity(Kg) | Distance |
|---|---|---|---|---|---|---|
| 1 | 2 | 12 | 3 | 6000 | [0.0, 8.0, 0.0, 8.0, 8.0] | 60 |
| 2 | 2 | 12 | 3 | 12000 | [0.0, 8.0, 0.0, 8.0, 8.0] | 56.4 |
| 3 | 2 | 24 | 3 | 6000 | [0.0, 16.0, 0.0, 16.0, 16.0] | 60 |
| 4 | 3 | 12 | 2 | 12000 | [0.0, 12.0, 0.0, 12.0, 12.0] | 79.2 |
| 5 | 3 | 24 | 2 | 6000 | [0.0, 24.0, 0.0, 24.0, 24.0] | 79.2 |

Weather time window 2 ,Flying time window 5

| | K | Q | Cn | $P_{max}$ | Customer received quantity(Kg) | Distance |
|---|---|---|---|---|---|---|
| 1 | 3 | 24 | 2 | 12000 | [0.0, 24.0, 0.0, 24.0, 24.0] | 79.2 |
| 2 | 2 | 24 | 3 | 6000 | [0.0, 16.0, 0.0, 16.0, 16.0] | 60 |
| 3 | 2 | 24 | 3 | 12000 | [0.0, 16.0, 0.0, 16.0, 16.0] | 60 |
| 4 | 3 | 12 | 2 | 6000 | [0.0, 12.0, 0.0, 12.0, 12.0] | 79.2 |
| 5 | 3 | 12 | 1 | 6000 | [0.0, 12.0, 0.0, 12.0, 12.0] | 52.8 |

Best solutions for first 5 flying time windows for cluster 2

Weather time window 1, Flying time window 1

| | K | Q | Cn | $P_{max}$ | Customer received quantity(Kg) | Distance |
|---|---|---|---|---|---|---|
| 1 | 3 | 24 | 2 | 6000 | [36.0,0.0,36.0,0.0,0.0] | 72 |
| 2 | 2 | 24 | 2 | 6000 | [24.0,0.0,24.0,0.0,0.0] | 48 |
| 3 | 3 | 12 | 2 | 12000 | [18.0,0.0,18.0,0.0,0.0] | 72 |
| 4 | 3 | 24 | 1 | 6000 | [24.0,0.0,48.0,0.0,0.0] | 55.2 |
| 5 | 3 | 12 | 1 | 6000 | [24.0,0.0,12.0,0.0,0.0] | 55.2 |

Weather time window 1, Flying time window 2

| | K | Q | Cn | $P_{max}$ | Customer received quantity(Kg) | Distance |
|---|---|---|---|---|---|---|
| 1 | 2 | 24 | 2 | 6000 | [24.0,0.0,24.0,0.0,0.0] | 48 |
| 2 | 2 | 24 | 2 | 12000 | [24.0,0.0,24.0,0.0,0.0] | 48 |
| 3 | 3 | 24 | 1 | 6000 | [48.0,0.0,24.0,0.0,0.0] | 50.4 |
| 4 | 2 | 12 | 2 | 6000 | [12.0,0.0,12.0,0.0,0.0] | 48 |
| 5 | 3 | 12 | 1 | 6000 | [24.0,0.0,12.0,0.0,0.0] | 55.2 |

Weather time window 1, Flying time window 3

| | K | Q | Cn | $P_{max}$ | Customer received quantity(Kg) | Distance |
|---|---|---|---|---|---|---|
| 1 | 3 | 24 | 1 | 6000 | [48.0,0.0,24.0,0.0,0.0] | 50.4 |
| 2 | 3 | 12 | 1 | 6000 | [24.0,0.0,12.0,0.0,0.0] | 55.2 |
| 3 | 3 | 24 | 1 | 12000 | [48.0,0.0,24.0,0.0,0.0] | 50.4 |
| 4 | 3 | 12 | 1 | 12000 | [24.0,0.0,12.0,0.0,0.0] | 55.2 |

Weather time window 2, Flying time window 3

| | K | Q | Cn | $P_{max}$ | Customer received quantity(Kg) | Distance |
|---|---|---|---|---|---|---|
| 1 | 2 | 24 | 2 | 6000 | [24.0,0.0,24.0,0.0,0.0] | 48 |
| 2 | 2 | 24 | 2 | 12000 | [24.0,0.0,24.0,0.0,0.0] | 48 |
| 3 | 3 | 24 | 1 | 6000 | [48.0,0.0,24.0,0.0,0.0] | 50.4 |
| 4 | 2 | 12 | 2 | 12000 | [12.0,0.0,12.0,0.0,0.0] | 48 |
| 5 | 3 | 12 | 1 | 6000 | [24.0,0.0,12.0,0.0,0.0] | 55.2 |

Weather time window 2 ,Flying time window 5

| | K | Q | Cn | $P_{max}$ | Customer received quantity(Kg) | Distance |
|---|---|---|---|---|---|---|
| 1 | 3 | 24 | 2 | 12000 | [36.0,0.0,36.0,0.0,0.0] | 72 |
| 2 | 2 | 24 | 2 | 6000 | [24.0,0.0,24.0,0.0,0.0] | 48 |
| 3 | 3 | 12 | 2 | 6000 | [18.0,0.0,18.0,0.0,0.0] | 72 |
| 4 | 3 | 24 | 1 | 12000 | [48.0,0.0,24.0,0.0,0.0] | 50.4 |
| 5 | 3 | 12 | 1 | 6000 | [24.0,0.0,12.0,0.0,0.0] | 55.2 |

Best admissible sequence of submissions among all possible sequence of submissions

| Flying time window | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Chosen submission | $S_{4,2,1}$ | $S_{5,1,2}$ | $S_{2,1,3}$ | $S_{5,1,4}$ | $S_{4,2,5}$ |
| Selected Submission | R 1 [0, 1, 0]<br>P [0, 8, 16]<br>R 2 [0, 3, 0]<br>P[0, 7, 14]<br>R 3 [0, 3, 0]<br>P [15, 22, 29] | R 1 [0, 2, 4, 5, 0]<br>P [90, 98, 106,113,119]<br>R 2 [0, 2, 4, 5, 0]<br>P [99, 107, 155,122,128] | R 1 [0, 2, 0]<br>P [130, 138, 146]<br>R 2 [0, 4, 0]<br>P [130, 138, 146]<br>R 3 [0, 5, 0]<br>P [130, 136, 142] | R 1 [0, 2, 4, 0]<br>P [160, 168, 176,184]<br>R 2 [0, 4, 5, 0]<br>P [160, 168, 175,181]<br>R 3 [0, 2, 5, 0]<br>P [177, 185, 193,199] | R 1 [0, 1, 0]<br>P[200, 208, 216]<br>R 2 [0, 3, 0]<br>P [200, 207, 214]<br>R 3 [0, 1, 0]<br>P [217, 225, 233] |
| CS Level of the submission | [33.3, 0.0, 66.6, 0.0,0.0] | [0.0, 33.3.0, 0.0, 33.3,33.3] | [0.0, 33.3.0, 0.0, 33.3,33.3] | [0.0, 33.3.0, 0.0, 33.3,33.3] | [66.7, 0.0, 33.7, 0.0,0.0] |

| Total distance | Final customer satisfaction |
|---|---|
| 316.4 | [100.0, 100.0, 100.0, 100.0,100.0] |

Legend: *K*- Fleet size, Q- Maximum loading capacity of UAV, $P_{max}$ - Maximum energy capacity of UAV , *Cn*- Number of customers per route

Fig. 3 Results of the experiments


Bocewicz, G., Nielsen, P., Banaszak, Z. and Thibbotuwawa, A. (2018) 'A Declarative Modelling Framework for Routing of Multiple UAVs in a System with Mobile Battery Swapping Stations', Communications in Computer and Information Science, Vol 920. Springer, pp. 73–88.

Bocewicz, G., Nielsen, P., Banaszak, Z. and Thibbotuwawa, A. (2019) 'Deployment of Battery Swapping Stations for Unmanned Aerial Vehicles Subject to Cyclic Production Flow Constraints', Intelligent Systems in Production Engineering and Maintenance. Vol. 835, pp. 429–441.

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, pp. 1–16. doi: 10.1109/TSMC.2016.2582745.

Geyer, C., Singh, S. and Chamberlain, L. (2008) 'Avoiding Collisions Between Aircraft : State of the Art and Requirements for UAVs operating in Civilian Airspace'.

Ham, A. M. (2018) 'Integrated scheduling of m-truck, m-drone, and m-depot constrained by time-window, drop-pickup, and m-visit using constraint programming', Transportation Research Part C: Emerging Technologies. Elsevier, 91(March), pp. 1–14.

Liu, X. F., Guan, Z. W., Song, Y. Q. and Chen, D. S. (2014) 'An optimization model of UAV route planning for road segment surveillance', Journal of Central South University, 21(6), pp. 2501–2510.

Maza, I. and Ollero, A. (2007) 'Multiple UAV cooperative searching operation using polygon area decomposition and efficient coverage algorithms BT - Distributed Autonomous Robotic Systems 6', in Alami, R., Chatila, R., and Asama, H. (eds). Springer Japan, pp. 221–230.

Rubio, J. C. and Kragelund, S. (2003) 'The trans-pacific crossing: long range adaptive path planning for UAVs through variable wind fields', in Digital Avionics Systems Conference, 2003. DASC'03. The 22nd. IEEE, p. 8–B.

Song, B. D., Park, K. and Kim, J. (2018) 'Persistent UAV delivery logistics: MILP formulation and efficient heuristic', Computers and Industrial Engineering, 120, pp. 418–428. doi: 10.1016/j.cie.2018.05.013.

Su, F., Li, Y. and Lincheng, S. (2009) 'An improved ant colony algorithm for UAV route planning in complex battlefield environment', Control and Decision Conference, 2009. CCDC '09. Chinese, pp. 3568–3573.

Thibbotuwawa A., Nielsen P., Bocewicz G. and Banaszak Z., (2019) 'UAVs Fleet Mission Planning Subject to Weather Fore-Cast and Energy Consumption Constraints' Automation 2019. Advances in Intelligent Systems and Computing, vol 920. Springer, Cham.

Wang, H., Lyu, W., Yao, P., Liang, X. and Liu, C. (2015) 'Three-dimensional path planning for unmanned aerial vehicle based on interfered fluid dynamical system', Chinese Journal of Aeronautics. Chinese Society of Aeronautics and Astronautics, 28(1), pp. 229–239.

Yang, G. and Kapila, V. (2002) 'Optimal path planning for unmanned air vehicles with kinematic and tactical constraints', in Proceedings of the 41st IEEE Conference on Decision and Control, 2002., pp. 1301–1306 vol.2.