Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

UAVs fleet mission planning robust to changing weather conditions

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Abstract: A fleet of homogeneous UAVs fly in a 2D plane matching a distribution network to service customers in a collision-free manner. Limited UAVs' battery capacity and UAVs' weight reduction during they traveling along planned routes and goods delivery as well as changing weather conditions are also taken into account. The goal is to determine a set of routings covering all delivery points so that the total distance traveled by the UAVs fleet is constrained by a battery capacity limit. All customers' demands are realized within a given time horizon and take into account forecasted weather constraints, focusing on changes in a wind speed and direction. In this context, the main objective is to propose a declarative model allowing one to prototype proactive routings of UAVs fleet mission. Computational experiments assessing alternative strategies of UAVs fleet mission robust to forecast weather conditions are discussed.

Keywords: UAVs fleet routing and scheduling, UAVs fleet mission planning, robustness to changing weather conditions.

1. INTRODUCTION

It is worth noting that a UAV's performance is highly influenced by the payload it is carrying, especially its weight reduction observed along subsequent deliveries as well as the weather conditions in which it is operating (wind may limit the number of target locations served, and low temperatures may adversely affect battery performance), and the non-linearity of fuel consumption. Consequently, the possibility of taking into account the influence of weather conditions on energy consumption, and hence, on the customer-servicing route and schedule, provides the basis for the construction of a model that allows searching for missions that are robust to specific weather changes.

Because considered UAVs routing problems are NP-hard, their solutions in real-life cases are only approximate. This means that approximate calculation techniques derived from artificial intelligence methods have to be used, especially employing a declarative representation following constraints programming paradigm. In this context, the approach developed in this study, which is implemented in a constraint programming environment, assumes that the energy consumption is a non-linear function that depends on weather conditions, carrying payload, UAV "geometry" and the flight trajectory (Thibbotuwawa et al. 2019; Rucco et al. 2016; Kim et al. 2018; Rubio and Kragelund 2003).The goal is to find proactive flight mission plans (routings and schedules), which are collision-free and guarantee the providing the right quantity of goods ordered by all customers in a given time horizon by a fleet of UAVs with an energy capacity limit, flying under forecasted weather conditions.

The problem considered in this study can be perceived as a continuation of issues raised in our earlier works (Thibbotuwawa et al. 2019, Bocewicz et al. 2019, Thibbotuwawa, Nielsen et al. 2019) and boils down to the following UAVs fleet mission planning assuming a given fleet size and a set of spatially dispersed target points specified by the volume of expected deliveries and the coordinates of their location. The known arrangement of delivery points allows to determine the amount of energy consumed during flight from one drop-off point to another. Under these assumptions, the following question is stated: What is the UAVs fleet size that fulfills all deliveries expected by recipients within an assumed time horizon while taking into account battery constraints and forecasted changes in a wind speed predicted for the UAV fleet while maximizing the total volume of deliveries? The interactive answer to this question (e.g., supported by dedicated decision support systems) might facilitate mission definition, pre-flight 3D synthetic mission visualization and flight evaluation.

The paper is organized as follows: Section 2 provides an overview of the literature. A motivation example introducing to the problem under consideration is presented in Section 3. A reference model for a UAV fleet mission planning is presented in Section 4. The Constraint Satisfaction Problem (CSP) aimed at UAVs fleet delivery mission planning is formulated in Section 5. An example illustrating the performance of the proposed approach is given in Section 6. The key conclusions are formulated and the main directions of future research are suggested in Section 7.

2. LITERATURE REVIEW

The task of mission planning is to find a sequence of waypoints that connect the start to the destination location. Usually, the designed mission plans are analyzed from multiple perspectives including changing weather conditions (usually wind speed and direction), payload and energy capacities of UAVs, fleet sizes, the number of customers visited by a UAV on a mission and delivery performance (Rubio and Kragelund

2003; Liu et al. 2014; Khosiawan et al. 2014; Dorling et al 2017; Sitek and Wikarek 2019).

UAVs are already being explored as useful tools in multiple civil scenarios (Besada et al. 2018; Eun et al. 2019; Roca-Riu and Menendez 2019). In many cases, UAV-based systems are required to deliver functionalities such as surveillance and reconnaissance, monitoring (e.g., like inspection services in the agriculture), mapping and photogrammetry, automatic fault detection or inventory tasks. As well as to other areas, like military (Royset and Reber 2010; Evers et al. 2014) and above-mentioned civilian applications, also to be counted the use of UAVs for logistic deliveries including urban fixed infrastructure, like distribution centers or depots networks (Gilmore et al. 2019; Roca-Riu and Menendez 2019; Thibbotuwawa et al. 2019; Coelho et al. 2017; Tian et al. 2006; Gola and Kłosowski 2018).

In each of these applications, the so-called pre-flight conflict detection and resolution methods that generate conflict-free paths for UAVs before the actual flight play a crucial role (Abdallah 2019,8). Models used for this purpose include representations implementing formalisms of MLP (Albert et al. 2017) declarative modelling (Thibbotuwawa et al. 2019), computer simulation (Wei et al. 2013), AI such as multi-agent (Ho et al. 2019), fuzzy logic (Suma and Murugesan 2019), heuristic searching (Roca-Riu and Menendez 2019), and so on.

Various technical and environmental factors influence the potential search for possible UAV mission planning solutions. These factors encompass the technical parameters of UAVs (UAV dimensions, battery capacity and carrying payload limit) and the environmental aspects of the changing weather conditions, including the wind speed, wind direction and air density and temperature. Existing research has largely ignored the impact of weather conditions by using linear approximations for energy (Dorling et al. 2017). There is little knowledge on how the above-mentioned parameters can affect solutions to UAV mission planning problems, even with reference to deterministic approaches (Thibbotuwawa et al. 2019). The existing literature also fails to provide solutions that would accommodate the effects of changing weather conditions on energy consumption in UAVs. Therefore, this study focuses on designation of feasible UAV fleet routes with schedules being derived subject to weather-dependent energy consumption constraints, and UAVs' weight reduction when flying along planned routes as well as forecast changes in weather conditions focusing on wind direction and wind speed.

3. A MOTIVATION EXAMPLE

Consider the distribution network covering 100 km^2 where 7 nodes are distinguished (one base: N_1 and 6 customers: $N_2 - N_7$) and serviced by fleet composed of two homogeneous UAVs - see Fig. 1. UAVs are specified by technical parameters collected in Tab. 1.

Let us assume that each customer requires the same kind of goods and the same quantity - 30 kg. All their demands should be satisfied within the prescribed time horizon equal to 2500 s while goods are transported under assumed weather conditions specified by vector of wind $\overrightarrow{W} = [vw, \theta]$ where: wind speed $vw = 12$ and wind direction $\theta = 120°$. Moreover, the effect of a reduced UAV weight caused by successive unloading of deliveries should be taken into account while one of the following two strategies assuming either UAV' constant ground speed or UAV' constant airspeed might be implemented (Thibbotuwawa et al. 2019; Rucco et al. 2016; Kim et al. 2018).

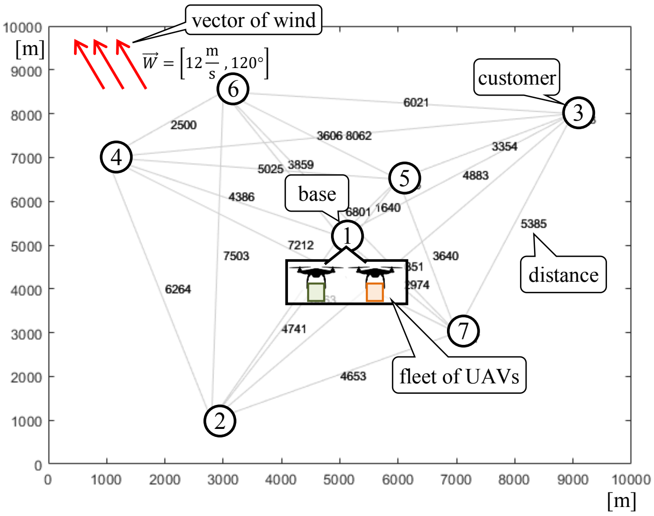

Fig. 1 Layout of distribution network

Tab. 1 Technical parameters specifying homogenous UAVs.

Technical parameters of UAVs	Value	Unit
Payload capacity Q	90	kg
Battery capacity CAP	5000	kJ
Airspeed va	20	m/s
Drag coefficient C_D	0.54	-
Front surface of UAV A	1.2	m
UAV width b	8.7	m

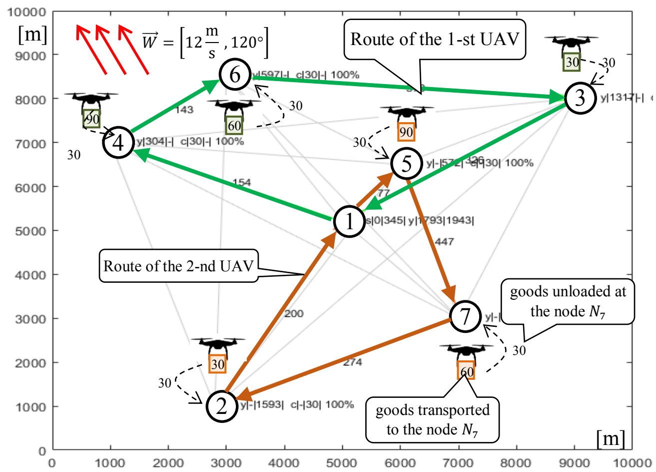

Fig. 2 Two UAV delivery routes

The problem under consideration boils down to the following question: Do the available UAVs fleet guarantees the delivery of required quantity of goods in the given transport network under assumed weather conditions changing within the assumed time horizon?

The computed flight routes: $\pi_1 = (N_1, N_4, N_6, N_3, N_1\,), \pi_2 = (N_1, N_5, N_7, N_2, N_1\,)$, (see Fig. 2) obtained for the assumed weather conditions $\overrightarrow{W}$ while employing strategy assuming UAV' constant airspeed ($va = 20\ m/s$), guarantee that the all demanded quantity of goods are delivered to customers.

The obtained solution has been analysed in terms of sensitivity to the amount of energy consumption in various weather conditions assuming that the wind direction may change in the range from $\theta = 0°$ to $\theta = 360°$ and a wind speed in the range from $vw = 0$ m/s to $vw = 20$m/s. Fig. 3 shows radar chart illustrating the contour lines which determine the maximum value of the wind speed function (i.e., function parameterized by the wind direction) guaranteeing the fulfilment of all planned deliveries using the specified battery capacity limit in the ranger from 50% to 100% of $CAP = 5000$ kJ.

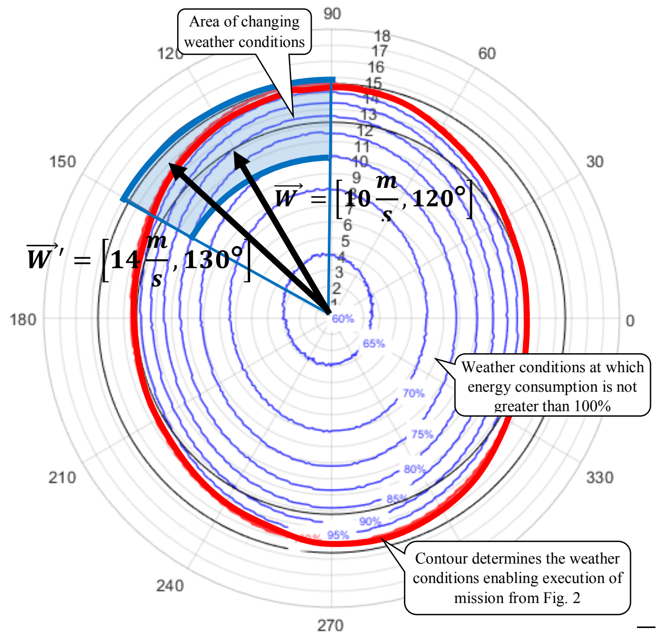

Fig. 3 Radar chart of resistance to changes in the wind speed following strategy assuming UAV' constant airspeed ($va = 20\ m/s$).

The contour lines connect the points of equal value of consumption energy. In that context the blue contour lines determine the area of weather conditions for which execution of the mission from Fig. 2 can be fulfilled within the range from 50% to 100% of battery capacity limit CAP=5000 kJ. In turn, the red contour line determines the weather conditions enabling execution of feasible the missions from Fig 2. Crossing this line means that at least one of the UAVs exceeds 100% of battery capacity limit, i.e., CAP=5000 kJ. In other words the radar charts from Fig. 3 illustrate how the obtained mission form the Fig. 2 is resistant to various weather conditions.

In order to assess the resistance of the obtained solution to changes in weather conditions, let us consider the situation in which the wind $\overrightarrow{W}$ may change within the following ranges: wind speed $vw \in \left[10\frac{\mathrm{m}}{\mathrm{s}}, 15\frac{\mathrm{m}}{\mathrm{s}}\right]$ and wind direction $\theta \in [90°, 150°]$. Note that UAVs routes from Fig. 2 guarantee planned delivery for weather conditions specified by $\overrightarrow{W} = [12\frac{\mathrm{m}}{\mathrm{s}}, 120°]$. However, no longer guarantee this under other weather conditions from considered ranges. For instance, it can be seen in Fig. 3 that when the wind speed exceeds 14 m/s for the direction $\theta = 130°$ (see vector $\overrightarrow{W}' = [14\frac{\mathrm{m}}{\mathrm{s}}, 130°]$) then the completion of the planned mission will be interrupted due to exceeding the amount of energy consumed, i.e. vector $\overrightarrow{W}'$ exceeds the limits set by red contour line. Naturally, the following question arises: Is there an alternative mission implemented along other set of routes that guarantees the completion of planned deliveries within a given time horizon in the given range of weather conditions ($vw \in \left[10\frac{\mathrm{m}}{\mathrm{s}}, 15\frac{\mathrm{m}}{\mathrm{s}}\right]$; $\theta \in [90°, 150°]$)?

In other words, what we are looking for is a proactive flight mission plan (determining UAV routes and schedules) which will allow a fleet of UAVs with an energy capacity limit, flying in given weather conditions, to deliver the required quantity of goods within assumed time horizon.

4. MODELING

4.1 Assumptions

In general the considered problem may be formulated as follows: Given a set of customers located at different points of assumed distribution network. Customers have to be serviced by a fleet of UAVs during a specified time horizon, under a changing weather while fulfilling the following assumptions:

- The weather forecast is known in advance with sufficient accuracy. The weather is specified by vector $\overrightarrow{W} = [vw, \theta]$ where vw is the wind speed and θ is the direction of wind.
- Network consists of customer locations (delivery points) and flying corridors.
- Every route travelled starts and terminates within a given time horizon.
- All UAVs are charged to their full energy capacity before the start of a flying time window, and one UAV can only fly one time during a flying time window.
- The same kind of cargo is delivered to different customers in different amounts [kg].
- The weight of an UAV is decreased as the cargo is successively unloaded at subsequent customers located along its route.
- The airspeed is constant throughout the mission. The ground speed is different for different segments and depends of the wind parameters specified by $\overrightarrow{W_l}$.

4.2 Declarative model

The mathematical formulation of the proposed model employs the following parameters, variables, sets and constraints:

Parameters

Distribution Network

$G = (N, E)$	graph of a transportation network: $N = \{1 \ldots n\}$ is a set of nodes, $E = \{\{i,j\} \mid i,j \in N, i \neq j\}$ is a set of edges
z_i	demand at node $i \in N$, $z_1 = 0$
$d_{i,j}$	travel distance from node i to node j
$t_{i,j}$	travel time from node i to node j

w time spent on take-off and landing of a UAV
ts time interval at which UAVs can take off from the base
$b_{\{i,j\};\{\alpha,\beta\}}$ binary variable corresponding to crossed edges.

$$\boldsymbol{b}_{\{i,j\};\{\alpha,\beta\}} = \begin{cases} \mathbf{1} & \text{when edges } \{i,j\} \text{ and } \{\alpha,\beta\} \text{ are crossed} \\ \mathbf{0} & \text{otherwise.} \end{cases}$$

UAV Technical Parameters

K size of the fleet of UAVs
Q maximum loading capacity of a UAV
C_D aerodynamic drag coefficient of a UAV
A front facing area of a UAV
ep empty weight of a UAV
D air density
b width of a UAV
CAP maximum energy capacity of a UAV

Environmental Parameters

H time horizon $H = [0, t_{max}]$
vw wind speed
θ wind direction
$va_{i,j}$ airspeed of a UAV traveling from node i to j
$\varphi_{i,j}$ heading angle, angle of the airspeed vector when the UAV travels from node i to node j
$vg_{i,j}$ ground speed of a UAV travelling from node i to node j
$\vartheta_{i,j}$ course angle, angle of the ground speed vector when the UAV travels from node i to j

Decision Variables

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

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

y_i^k time at which the k^{th} UAV arrives at node i
c_i^k weight of freight delivered to node i by the k^{th} UAV
$f_{i,j}^k$ weight of freight carried from node i to node j by the k^{th} UAV
$P_{i,j}^k$ energy per unit of time, consumed by k^{th} UAV during a flight from node i to node j
s^k take-off time of the k^{th} UAV
cp_i total weight of freight delivered to node i
π_k route of the k^{th} UAV
$\pi_k = (v_1, \dots, v_i, v_{i+1}, \dots, v_\mu)$, $v_i \in N$, $x_{v_i,v_{i+1}}^k = 1$

Sets

Y^k set of times y_i^k – schedule of the k^{th} UAV
Y family of Y^k – schedule of UAV fleet
C^k set of c_i^k, payload delivered by the k^{th} UAV
C family of C^k
Π set of UAV routes π_k
S UAVs mission $S = (\Pi, Y, C)$

Constraints

Routes. Relationships between the decision variables describing moments of commencement of operations forming the missions of individual UAVs as well as relationships linking moments of deliveries completion:

$$s^k \geq 0, k = 1 \dots K \quad (1)$$
$$(k \neq q) \Rightarrow (|s^k - s^q| \geq TS), k, q = 1 \dots K \quad (2)$$
$$\sum_{j=1}^{n} x_{1,j}^k = 1, k = 1 \dots K \quad (3)$$
$$(x_{1,j}^k = 1) \Rightarrow (y_j^k = s^k + t_{1,j}), j = 1 \dots n;\ k = 1 \dots K \quad (4)$$
$$(k \neq q \wedge y_i^k \neq 0 \wedge y_i^q \neq 0) \Rightarrow (|y_i^k - y_i^k| \geq w) \quad (5)$$
$$(x_{i,j}^k = 1) \Rightarrow (y_j^k = y_i^k + t_{i,j} + w) \quad (6)$$
$$y_i^k \geq 0, i = 1 \dots n;\ k = 1 \dots K \quad (7)$$
$$\sum_{j=1}^{n} x_{i,j}^k = \sum_{j=1}^{n} x_{j,i}^k, i = 1 \dots n;\ k = 1 \dots K \quad (8)$$
$$y_i^k \leq t_{max} \times \sum_{j=1}^{n} x_{i,j}^k, i = 1 \dots n;\ k = 1 \dots K \quad (9)$$
$$x_{i,i}^k = 0, i = 1 \dots n;\ k = 1 \dots K \quad (10)$$

Collision avoidance. Intersecting edges ($b_{\{i,j\};\{a,b\}} = 1$) cannot be occupied by more than one UAV at the same time ($x_{i,j}^k = 1, x_{i,j}^q = 1$).

$$(block_{\{i,j\}\{a,b\}} \wedge x_{i,j}^k = 1 \wedge x_{a,b}^q = 1) \Rightarrow (y_b^q \leq y_j^k - t_{i,j}) \vee (y_j^k \leq y_b^q - t_{a,b}), i,j = 1 \dots n;\ k,q = 1 \dots K;\ k \neq q \quad (11)$$

Delivery of freight. Relationships between variables describing the amount of freight delivered to nodes by UAVs and the demand for goods at a given node:

$$c_i^k \geq 0, i = 1 \dots n;\ k = 1 \dots K \quad (12)$$
$$c_i^k \leq Q \times \sum_{j=1}^{n} x_{i,j}^k, i = 1 \dots n;\ k = 1 \dots K \quad (13)$$
$$\sum_{i=1}^{n} c_i^k \leq Q, k = 1 \dots K \quad (14)$$
$$(x_{i,j}^k = 1) \Rightarrow c_j^k \geq 1, k = 1 \dots K;\ i = 1 \dots n;\ j = 2 \dots n \quad (15)$$
$$\sum_{k=1}^{K} c_i^k = cp_i, i = 1 \dots n \quad (16)$$
$$cp_i = z_i, i = 1 \dots n \quad (17)$$
$$\sum_{i=1}^{n} c_i^k = cs^k, k = 1 \dots K \quad (18)$$
$$(x_{1,j}^k = 1) \Rightarrow (fc_j^k = cs^k), j = 1 \dots n;\ k = 1 \dots K \quad (19)$$
$$(x_{i,j}^k = 1) \Rightarrow (fc_j^k = fc_i^k - c_i^k) \quad (20)$$
$$(x_{1,j}^k = 1) \Rightarrow (f_{1,j}^k = cs^k), j = 1 \dots n;\ k = 1 \dots K \quad (21)$$
$$(x_{i,j}^k = 1) \Rightarrow (f_{i,j}^k = fc_j^k),\ i,j = 1 \dots n;\ k = 1 \dots K \quad (22)$$

Energy consumption. The amount of energy needed to complete tasks performed by an UAV cannot exceed the maximum capacity of its battery.

$$bat^k \leq CAP, k = 1 \dots K \quad (23)$$
$$\sum_{i=1}^{I} \sum_{j=1}^{I} x_{i,j}^k \times t_{i,j} \times P_{i,j}^k = bat^k, k = 1 \dots K \quad (24)$$
$$P_{i,j}^k = \frac{1}{2} C_D \times A \times D \times (va_{i,j})^3 + \frac{(ep + f_{i,j}^k)^2}{D \times b^2 \times va_{i,j}}, \quad (25)$$
$$t_{i,j} = \frac{d_{i,j}}{vg_{i,j}} \quad (26)$$
$$vg_{i,j} = \sqrt{(va_{i,j} cos\varphi_{i,j} + vw\, cos\theta)^2 + (va_{i,j} sin\varphi_{i,j} + vw\, sin\theta)^2} \quad (27)$$

$$\varphi_{i,j} = \vartheta_{i,j} - arcsin\left(\frac{vw}{va_{i,j}} sin\left(\theta - \vartheta_{i,j}\right)\right) \tag{28}$$

5. PROBLEM FORMULATION

The review of literature shows that there is a scarcity of effective solutions for planning UAV missions under changing weather conditions. In this context, in our new approach we consider the UAVs fleet of size K servicing the set of customers belonging to the distribution network G in the time horizon H. Consequently, the solution to the proposed planning problem boils down to the following question:

Does there exist mission S (determined by variables Π, Y, C) guaranteeing the delivery of all required quantity of goods under constraints related to energy consumption (23)–(28), collision avoidance (11), etc.?

The investigated problem can be seen as a Constraint Satisfaction Problem (CSP) (Bocewicz et al. 2019) given by (29):

$$CP = (\mathcal{V}, \mathcal{D}, \mathcal{C}) \tag{29}$$

where:

$\mathcal{V} = \{\Pi, Y, C\}$ – a set of decision variables determining mission S: Π – a set of UAV routes, Y – a schedule of a UAV fleet, C – a set of payload weights delivered by the UAVs,

$\mathcal{D}$ – a finite set of decision variable domain descriptions,

$\mathcal{C}$ – a set of constraints specifying the relationships between UAV routes, UAV schedules and transported materials (1)–(29).

To solve CP (29), one has to determine the values of the decision variables for which all the constraints hold. By implementing CP (29) in a constraint programming environment, such as IBM ILOG, one can build a computational engine to answer the previously formulated question.

6. COMPUTATIONAL EXPERIMENTS

Consider the case of UAVs fleet mission planning presented in Section 3. A delivery plan is sought such that it guarantees the completion of planned deliveries within a given time horizon (2500s) in the given range of changing weather conditions ($vw \in \left[10\frac{\text{m}}{\text{s}}, 15\frac{\text{m}}{\text{s}}\right]$; $\theta \in [90°, 150°]$). The source of the weather data is the database of Polish Institute of Meteorology and Water Management-National Research Institute.

Parameters of the two UAVs forming the fleet are summarized in the Tab. 1. The plan sought was obtained within 5 seconds in the declarative programming environment IBM ILOG (Intel Core i7-M4800MQ 2.7 GHz, 32 GB RAM). It does not guarantee that all planned deliveries will be carried out in given weather conditions. Assuming the worst-case scenario $\overrightarrow{W} = [15\frac{\text{m}}{\text{s}}, 150°]$, the energy consumption of the 1-st UAV (green color) will exceed the allowable value of 5000 kJ. In this situation the fleet size increase should be considered.

Therefore, the following two scenarios are worth considering:

Scenario 1: Setting a mission plan assuming the occurrence of variable weather conditions

To illustrate this scenario, consider the case of two drones described above. If by $t_B = 747s$ (the moment determining the date by which the 1-st UAV may still return to the base) the weather conditions will not improve (e.g. the wind speed vw will not reach below 12.2 m/s) then the decision is made to discontinue the mission and return the 1-st UAV to the base (see Fig. 4 – Fig.6). As can be seen in Fig. 4, the decision to discontinue the mission may occur when the 1-st UAV is in the node N_6. As a result of this decision, there is no planned delivery of goods to point N_3. Consequently, an additional 3-rd UAV mission is launched to meet this delivery, see the rote distinguished by blue color. As shown in Fig. 6, adopting this approach ensures that the energy consumption of each UAVs is kept below 5000 kJ. Of course, in a situation where the weather will improve until $t_B = 747s$ the mission can be continued using two UAVs.

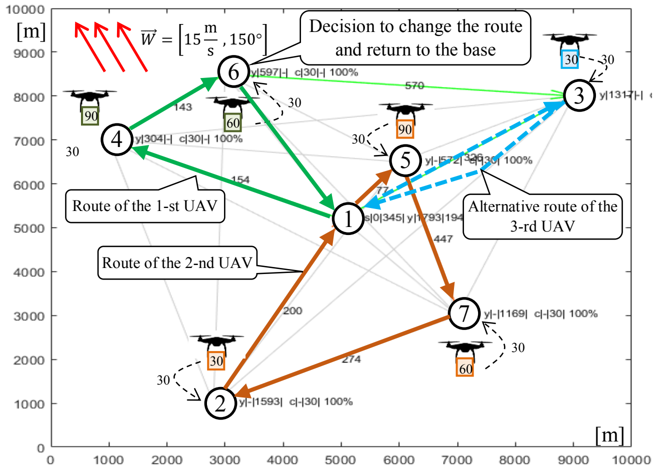

Fig. 4 Routes following scenario 1

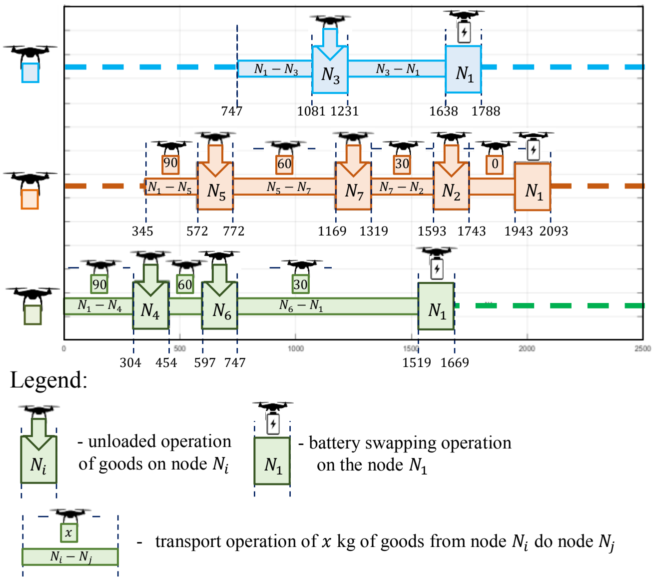

Fig. 5 Gantt chart for the mission from Fig. 4

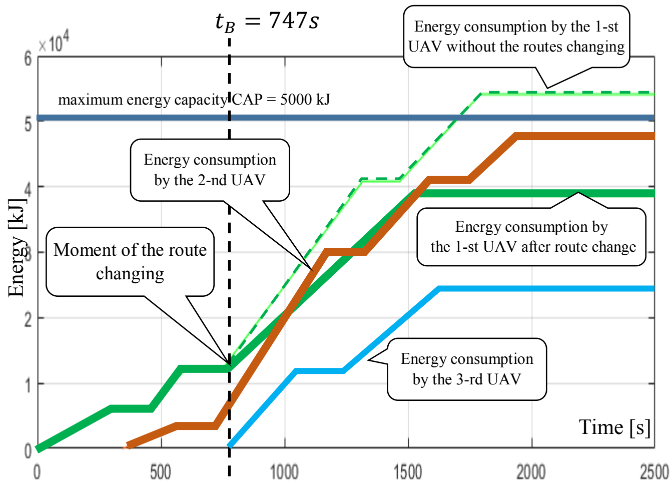

Fig. 6 The energy consumption of drones when changing routes according to Fig. 4

Scenario 2: Setting a mission plan assuming the existence of the worst weather conditions

In considered case this scenario assumes that the mission sought guarantees the completion of planned deliveries within a given time horizon 2500 s in the worst weather conditions: $\overrightarrow{W} = [15\frac{\text{m}}{\text{s}}, 150°]$. The designated mission being the solution to the CS (29) problem (obtained in 12.5 s) is carried out by a fleet of three UAVs specified by technical parameters from Tab. 1. Fig. 7 shows the computed flight routes: $\pi_1 = (N_1, N_4, N_6, N_1)$, $\pi_2 = (N_1, N_2, N_7, N_1)$, $\pi_3 = (N_1, N_5, N_3, N_1)$ guaranteeing that the demanded quantity of goods are delivered to customers under the given weather conditions.

As can be seen from Fig. 7, the mission received is resistant to the given range of weather conditions ($vw \in \left[10\frac{\text{m}}{\text{s}}, 15\frac{\text{m}}{\text{s}}\right]$; $\theta \in [90°, 150°]$. That means the considered vector $\overrightarrow{W}$ does not exceed the red contour line.

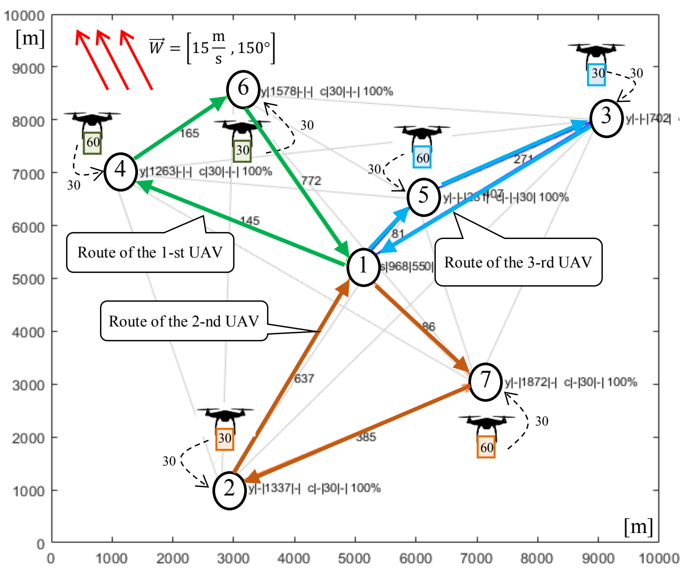

Fig. 7 Routings following scenario 2

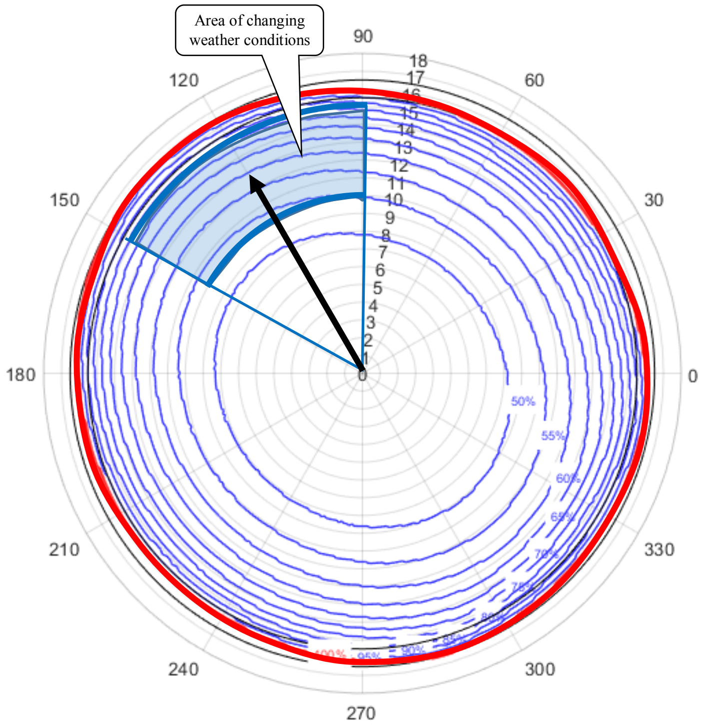

Fig. 8 Radar chart of resistance to changes in wind speed following the scenario 2.

7. CONCLUSIONS

Because considered UAVs routing problems are NP-hard, their solutions in real-life cases are only approximate. This means that approximate calculation techniques derived from artificial intelligence methods have to be used, especially employing a declarative representation following constraints a programming paradigm. The computer experiments performed in the present study confirmed the efficiency of the proposed modelling concept implemented in the UAV mission planning.

Two scenarios taking into account the influence of weather conditions on energy consumption of saving battery power aimed at searching for missions that are robust to specific weather changes were proposed. Special attention was paid to research focused on the sensitivity of the energy consumption due to the wind speed and direction changes.

In our future research on robust UAV mission planning, we aim at exploring the relationships linking the total distance traveled with the total travel time and the cost of saving battery power of an UAV fleet. A particular attention will be paid to the pick-up delivery problem with time windows and to planning the size of fleets composed of heterogeneous UAVs.

ACKNOWLEDGEMENTS

The work was partially supported by the National Science Centre, Poland under grant: UMO-2017/27/B/ST7/00620.

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