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Published in:
IFAC-PapersOnLine

DOI (link to publication from Publisher):
10.1016/j.ifacol.2022.04.236

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Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

Link to publication from Aalborg University

Citation for published version (APA):
Bocewicz, G., Radzki, G., Nielsen, P., & Banaszak, Z. (2022). UAVs' Dynamic Routing, Subject to Time Windows Variation. *IFAC-PapersOnLine*, *55*(2), 457-462. https://doi.org/10.1016/j.ifacol.2022.04.236

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IFAC PapersOnLine 55-2 (2022) 457–462

UAVs' Dynamic Routing, Subject to Time Windows Variation

Grzegorz Bocewicz*, Grzegorz Radzki*, Peter Nielsen**, Zbigniew Banaszak*

* *Faculty of Electronics and Computer Science, Koszalin University of Technology, Poland, grzegorz.bocewicz@tu.koszalin.pl, radzki.grzegorz@gmail.com, Zbigniew.Banaszak@tu.koszalin.pl*
** *Dept. of Materials and Production, Aalborg University, Aalborg, Denmark, peter@mp.aau.dk*

Abstract: This paper presents a method for the multiple autonomous vehicles mission flight planning in changing weather conditions. We model UAVs fleet servicing spatially-dispersed customers in terms of declarative modelling framework. The considered problem boils down to a predictive and reactive planning of delivery missions within a specified timeframe. Due to the need to implement an emergency return of a UAV to its base, or to handle variations in delivery periods, conditions sufficient to allow eliminating unfeasible solutions, and thus allowing to speed up the calculations, have been developed. The results of numerous computer experiments have confirmed experiments these expectations.

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Keywords: multiple autonomous vehicles mission flight planning, weathercast, alternative routing, constraint programming

1. INTRODUCTION

Multiple Unmanned Aerial Vehicles (UAVs) provide an attractive platform for various applications covering environmental and disaster monitoring, delivery services, agriculture and defiance. The specificity of these applications inspires new design solutions as well as new problems of planning and control UAVs fleets carrying out their missions in various atmospheric conditions (Cheikhrouhou and Khoufi 2021; Nigam and Kroo 2008; Shetty et al. 2008).

In this context the considered problem boils down to planning a mission of UAV within dynamic and unpredictable environmental constraints (Dorling et al. 2017; Patella et al. 2021; Troudi et al. 2018; Sung and Nielsen 2020; Enright et al. 2015). Most popular disruptions of UAVs missions are determined by the weather conditions (still changing), which may have an effect on consumption energy and shortening their range (Thibbotuwawa et al. 2019). This work focuses on reactive planning (Oubbati et al. 2020; Shirani et al. 2012) of deliveries by a UAV fleet, guaranteeing the mission robustness in context to unforeseen weather changes (e.g. changes of speed and direction wind) and notification/ cancelation the customer orders. In this context the problem is formulated as delivery time windows-constrained while limited by batteries discharging parameters the heterogeneous multi-UAV and multiple traveling salesman problem. To solve this NP-hard problem, a novel application of Constraint Programming (CP) approach is proposed in order to satisfy timely deliveries without UAVs batteries discharging. The proposed deterministic approach employing CP techniques which are very time-consuming due to the complexity of the calculations are adopted in only small instances. The advantage of this approach, however, is the possibility of simultaneous consideration of many different variables, and taking into account various constraints also including non-linear ones. The originality of presented contribution concerns a combination of proactive and reactive approaches in order to planning of UAV missions. The proposed model assumes that the constraint satisfaction problem (CSP) representing a considered problem allows an effective planning of UAV missions. Especially, this work provides the robustness function convexity, allowing acceleration of CSP solution. The main objective is to introduce a hybrid model of constraint programming, being a combination of proactive and reactive planning, to route a UAV fleet's delivery missions. Our contribution in this area comes down to: (*i*) using robustness function that allows to assess the fleet resistance to changes in the orders of impatient customers while operating in a highly-dynamic environment, (*ii*) presenting benefits following from implementation of the condition guaranteeing convexity of robustness function, and (*iii*) conducting numerous computer experiments confirming these expectations in terms of online planning of UAV fleets' missions.

The detailed paper structure is as follows: Section 2 presents the state of art. Section 3 provides a formal declarative model used then in the Section 4 devoted to the problem formulated in terms of the CSP while boiling down to reactive routing of the multiple autonomous vehicles mission. A paper is organized following. Section 2 presents the state of art. Section 3 presents the used methodology. Section 4 presents a declarative model for reactive planning of UAV missions. Section 5 presents multiple experiments conducted and obtained results. The conclusions are submitted in Section 6 .

2. STATE OF ART

A many number of research concern the various attribute of the construction (Ragab and Flores 2021; Palazzetti 2021; Ullah et al. 2019) and operation (Dorling et al. 2017; Sung and Nielsen 2020; Lohatepanont and Barnhart 2005; Thibbotuwawa et al. 2019; Wikarek et al. 2019) of UAVs, as well as the possibilities of UAVs using in different areas of civil (Shiri et al. 2021; Tariq et al. 2018) and military missions, as well as the methods for planning their missions, (Chadwick and Miller 2018) follow the trend of focusing their

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10.1016/j.ifacol.2022.04.236

research on the online planning of missions to be carried out by UAVs' teams. Here it is worth noting the growing interest in multiple UAV missions planning (Cheikhrouhou and Khoufi 2021; Nigam and Kroo 2008; Shetty et al. 2008). This trend has become more clearly noticeable. This area of research is widely featured in an Industry 4.0 covering many other subjects (Patalas-Maliszewska and Halikowski 2019; Kłosowski et al. 2018; Relich and Bzdyra 2015; Jasiulewicz-Kaczmarek et al. 2021; Patalas-Maliszewska and Kłos 2019). Other research cover a lot of fields of practical application e.g., patrolling (Traverso et al. 1996), package delivery (Troudi et al. 2018) and delivery communication capabilities (Ragab and Flores 2021), healthcare (Ullah et al. 2019; Shiri et al. 2021).This focus of the research also covers the issues of serving impatient customers (Bai et al. 2018; Sparaggis and Towsley 1994) whose ad hoc changes in decisions change the conditions for the receipt of planned orders and thus enforce the need to introduce appropriate corrections to the schedule of the planned mission. Both of research are united by the need for an integrated, i.e. combining the dimensions of time and space, decision-making. The vast majority of publications on the subject usually focus only on one of these threads. This means that, in most cases in the planning process, the constraints resulting from the technical capabilities of the available UAV fleet, and the restrictions resulting from the distributions of recipients, are taken into account. However, restrictions related to dynamic changes in the dates of receipts for ordered orders are omitted. This may lead to unnecessary searches for routes to recipients whose service in the changed dates prevents the UAV from returning to base safely.

In that context the considered problem can treated as an extension of Vehicle Routing Problem (VRP) which belongs to class of NP-hard problems (Levner et al. 2010; Kamoun and Sriskandarajah 1993). According to the current taxonomy, the methods for solving such problems can be partitioned into two main categories: approximation and exact methods (Stork et al. 2020). The approximation methods try to find the best possible solution while providing no guarantees on its quality, i.e., they prefer quick solutions over optimal ones. In turn, exact methods are guaranteed to find the best solution to the problem given enough time, i.e., they are oriented towards the search for the optimal solution at the expense of the time incurred to obtain it. In the approximation approach, some methods implement heuristic algorithms (e.g., metaheuristics driven like Variable Neighborhood Search (VNS), Simulated Annealing (SA), and Tabu Search (TS)) and population algorithms (such as Particle Swarm Optimisation (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC) and evolutionary algorithms, e.g., Memetic Algorithms (MMA), Genetic Algorithm (GA)) (Slowik and Kwasnicka 2020; Zhangjie et al. 2018). Exact approach leverage intelligent forms of enumerative search, such as Dynamic Programming (DP), Mixed Integer Linear Programming (MILP), Branch-and-Bound (BB), and Constraint Programming (CP) (Thibbotuwawa et al. 2019, Xue et al.2022).

Indicated research gaps were the inspiration for conducting this study, focusing on an extension of our previous research (Thibbotuwawa et al. 2019; Radzki et al. 2021), by the addition to developed model of two sufficient conditions which allow the ability to limit the searching space. The conditions that constitute this extension create the possibility, in an online mode, to foresee a UAV's battery depletion before it has completed its mission.

3. MULTIPLE AUTONOMOUS VEHICLES MISSION FLIGHT PLANNING

Let's consider a digraph $G = (N, E)$ modeling a distribution network. These kind of digraph G consist of the set of nodes (representing delivery points and base) $N = \{N_1, \dots, N_\lambda, \dots, N_n\}$ and edges $E = \{(N_\beta, N_\lambda) | \beta, \lambda \in \{1, \dots, n\}, \beta \neq \lambda\}$ (representing ways between the delivery points). The fleet of UAVs (U_k – means k-th UAV with capacity Q_k) transporting goods to delivery points is modeled by set $\mathcal{U} = \{U_1, \dots, U_k, \dots, U_K\}$. The value of variable $z_\lambda \in \mathbb{N}$ determines the quantity of goods transported to point N_λ. The following parameters are used to describe technical features of UAVs: airspeed (va), capacity of battery (CAP), width (b), drag coefficient (C_D), front surface A.

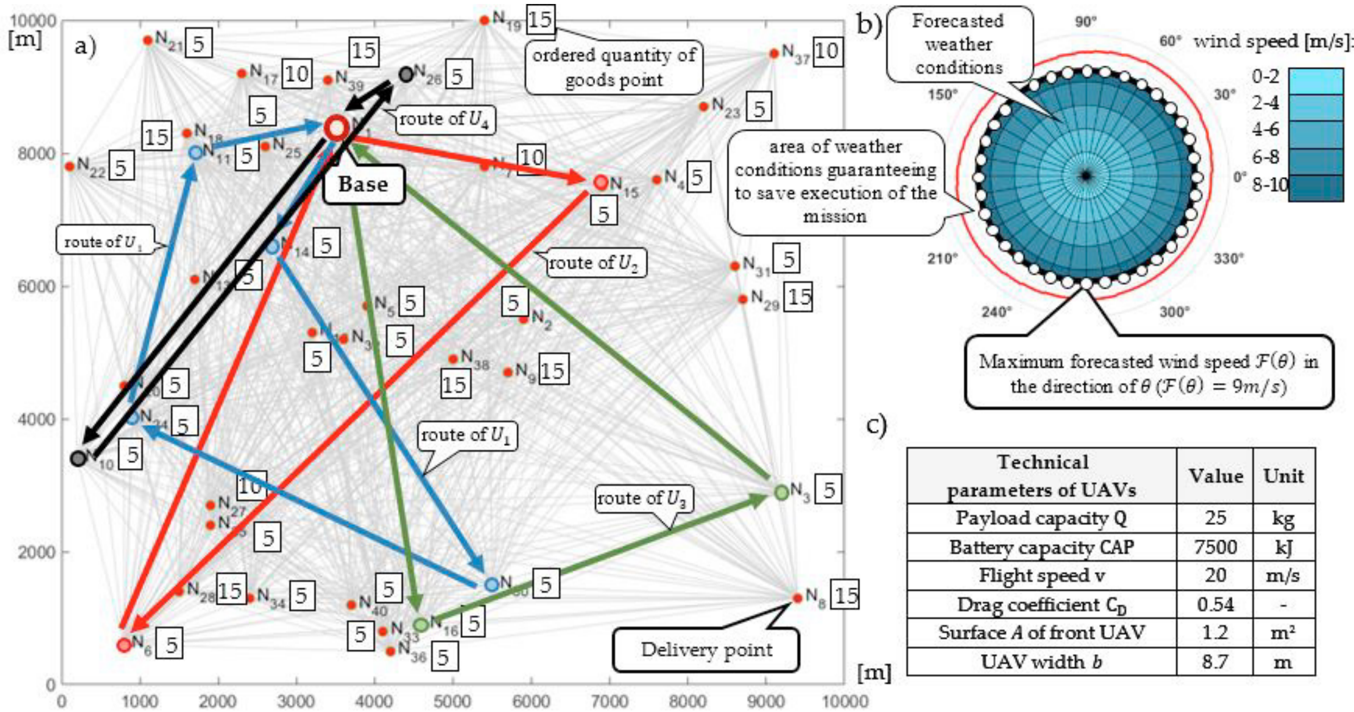
The delivery mission S of UAVs is divided into sub-missions ${}^{l}S$ covering the departure and return of each UAV to base. The value of the variable ${}^{l}c_\lambda^k \in \mathbb{N}$ means an amount of goods transported to point $N_\lambda$by U_k in sub-mission ${}^{l}S$.

The value variable ${}^{l}y_\lambda^k \in \mathbb{N}$ means the moment when the U_k arrives at the delivery point N_λ. In that context, the sequence ${}^{l}Y = ({}^{l}y_1^1, \dots, {}^{l}y_1^K, \dots, {}^{l}y_n^1, \dots, {}^{l}y_n^K)$ is the schedule of the UAVs fleet. In addition, each delivery point $N_\lambda \in ND$ is associated with the delivery time window $dX_\lambda = [dx_\lambda^{down}; dx_\lambda^{up}]$. In turn, the sequences: ${}^{l}\pi_k = (N_{k_1}, \dots, N_{k_i}, N_{k_{i+1}}, \dots, N_{k_\mu})$ where: $k_i \in \{1, .., n\}$, $(N_{k_i}, N_{k_{i+1}}) \in E$ is called further the route of U_k (executed during sub-mission ${}^{l}S$). In that context the sequence of routes ${}^{l}\Pi = ({}^{l}\pi_1, \dots, {}^{l}\pi_k, \dots, {}^{l}\pi_K)$ represents the completed deliveries during sub-mission ${}^{l}S$.

Usually the sub-mission ${}^{l}S$, defined as a four: ${}^{l}S = ({}^{l}\mathcal{U}, {}^{l}\Pi, {}^{l}Y, {}^{l}C)$ is performed under different weather. We assumed that the forecasted weather is described by the function $F(\theta)$ which values mean the upper bound of wind speed for direction θ. In turn, the function $\Upsilon_{k,l}(\theta)$ determines the values of wind speed, for which the delivery plan executed by the U_k guarantees that the UAV battery is not discharged.

It is assumed (Radzki et al. 2021) that the sub-mission ${}^{l}S$ is resistant to the forecasted weather if the boundary wind $\Upsilon_{k,l}(\theta)$ exceeds the function $F(\theta) : \Upsilon_{k,l}(\theta) \geq \mathcal{F}(\theta)$.

Moreover it is assumed that the disruptions IS may occur during the sub-mission ${}^{l}S$. The disruptions IS may be due to the changes in the weather, changes in delivery time windows $dX^*$and changes in the number of delivery points served. Taking the above into account, the problem considered can be defined following. Given is the delivery mission S in which a disruption IS (at the time t^*) appears. *Does a reroute mission S^* exist guaranteeing the timely deliveries without UAVs batteries discharging?*



Technical parameters of UAVs	Value	Unit
Payload capacity Q	25	kg
Battery capacity CAP	7500	kJ
Flight speed v	20	m/s
Drag coefficient C_D	0.54	-
Surface A of front UAV	1.2	m²
UAV width b	8.7	m

Fig. 1. Layout of the distribution network with UAVs' routes highlighted.

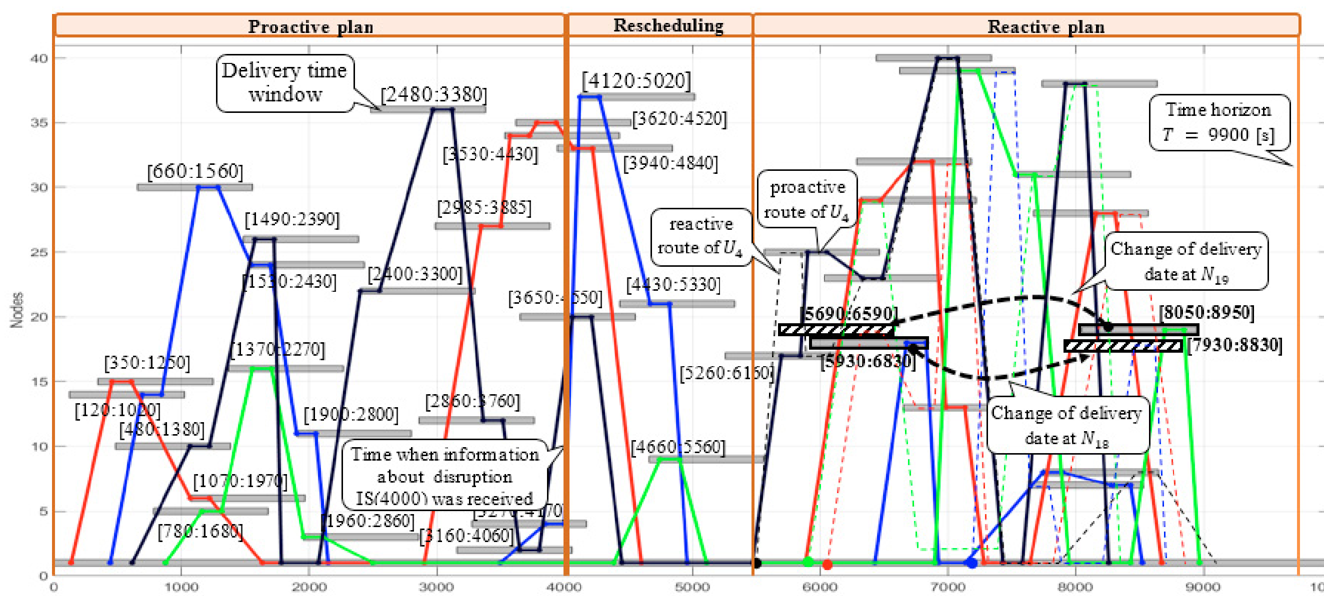


Fig. 2. Schedule of delivery missions for the fleet $\mathcal{U} = \{U_1, U_2, U_3, U_4\}$

Let's consider an example of distribution network from Fig. 1a) covering area 100 km² and containing 1 base (N_1) and 39 delivery points ($N_2, N_3, \ldots, N_{40}$). The goods are delivered by the fleet $\mathcal{U} = \{U_1, \ldots, U_4\}$. Technical parameters of UAVs are presented at the Fig. 1c). The weights of orders z_λ are presented in Fig. 1a) while the delivery time windows dX_λ are shown in Fig. 2. With these assumptions, the UAVs mission S plan, guaranteeing timely deliveries of the required amount of goods, is sought.

The example solution covers 9 sub-missions: $S = ({}^1S, \ldots, {}^9S)$ following the wind speed limitation 9 m/s (see Fig. 2.). The course of a UAV fleet's mission ${}^1S$: ${}^1\pi_1 = (N_1, N_{14}, N_{30}, N_{24}, N_{11}, N_1)$; ${}^1\pi_2 = (N_1, N_{15}, N_6, N_1)$; ${}^1\pi_3 = (N_1, N_5, N_{16}, N_3, N_1)$; ${}^1\pi_4 = (N_1, N_{10}, N_{26}, N_1)$ and the resistance function: $\Upsilon_{2,1}(\theta)$, is presented at Fig. 1. The time horizon is equal to 2.75 hours ($T = 9900$ [s]). Note that the presented mission is weatherproof (that means $\Upsilon_{k,l}(\theta) \geq 9\ m/s$).We consider a situation in which the delivery time windows at the delivery points N_{18} and N_{19} changed at the time of $t^* = 4000$ [s], i.e. the time windows $dX_{18} = [5930,6830]$, $dX_{19} = [8050,8950]$ have been changed to the following one $dX^*_{18} = [7930,8830]$, $dX^*_{19} = [5690,6590]$. Such a change means that this mission cannot be continued. In this situation, it is necessary to correct the route. We assumed that at the time $t^* = 4000$ is a sudden change in the delivery time windows assigned to the delivery points N_{18} and N_{19}, i.e. IS occurs, resulting in $dX^*_{18} = [7930,8830]$, $dX^*_{19} = [5690,6590]$.This leads to a following question*: Does a reroute plan exist S^*, that guarantees the timely delivery without UAVs batteries discharging?*

4. PROBLEM STATEMENT

In order to define the disruption $IS(t^*)$, let's consider the state of mission: $IS(t) = (M(t), \mathcal{F}^*(\theta,t), {}^*G(t), Z^*(t), dX^*(t))$, where: $M(t)$ is an UAVs allocation at the time t; $\mathcal{F}^*(\theta,t)$ is the weather forecasted at the time t;${}^*G(t)$ is a digraph representing network; $Z^*(t)$ is the sequence of goods requested at the time t and $dX^*(t)$ is the sequence of requested delivery time windows. Disruption $IS(t^*)$ occurring at t^* is the state following condition $[\mathcal{F}^*(\theta,t^*) \neq \mathcal{F}^*(\theta)] \vee [{}^*G(t^*) \neq G] \vee [Z^*(t^*) \neq Z] \vee [dX^*(t) \neq dX^*]$. In the case of the occurrence of disruptions the following conditions (if-then) rules are used:

1. Situation in which mission S is not robust to disruption $IS(t^*)$ implies a need to check the possibility of its adaptation to new conditions.
2. The UAV should return to the base in a situation where a disturbance $IS(t^*)$ prevents the continuation of its mission.
3. Situation in which handling of deliveries planned to be carried out by the UAV returning to the base cannot be implemented by other UAVs implies a need to check whether the reserve UAVs will be able to take an appropriate replacement
4. The activity of the reserve UAVs should be suspended in a situation where they cannot replace the UAVs returning to the base.

Effective response to disruptions (in accordance with above rules) it comes down to solving the constraint satisfaction problem $CS\left({}^{\bigcirc}\mathcal{U}, S,\ IS(t)\right)$ employing elements from tab. 1.

The following constraints describing the relationships between the variables from tab 1 (Radzki et al. 2021) can be distinguished :

- the relationship between routes (represented by ${}^l x^k_{\beta,\lambda}$) and the delivery schedule (${}^l y^k_\lambda$) at the same time guaranteeing deadlock-free and collision-free flight of UAVs as well as that the ordered goods are delivered to recipients within the agreed time windows $(dx^{up}_\lambda + {}^l y^k_\lambda \leq +w \leq dx^{down}_\lambda)$.
- constraints limiting the amounts of delivered goods (${}^l c^k_\lambda$) along each UAV route (${}^l x^k_{\beta,\lambda}$) as well as ensuring that UAVs are not overloaded while delivering the correct amounts of goods.
- constraints guaranteeing that the mission delivery plan S is safe i.e. resistance functions $\Upsilon_{k,l}(\theta)$ for the fleet $\mathcal{U}$ exceed the value of the function $Z(\theta)$: $\Upsilon_{k,l}(\theta) \geq \mathcal{F}(\theta)$. The constraints assume that the UAVs' battery consumptions are specified by nonlinear function from the weight of freight ${}^l f^k_{\beta,\lambda}$, ground speed $vg_{\beta,\lambda}$ and wind speed vw.

Table. 1 Parameters and decision variables

Parameters	
${}^lG$	graph of a distribution network for sub-mission ${}^lS$
z_λ	demand at node N_λ, $z_1 = 0$
dX_λ	delivery time window $dX_\lambda = \left[dx^{down}_\lambda; dx^{up}_\lambda\right]$ for N_λ
$d_{\beta,\lambda}$	distance between N_β, N_λ
$t_{\beta,\lambda}$	travel time between N_β, N_λ
w	time spent on take-off and landing of a UAV
Q	maximum loading capacity
H	time horizon
$\Upsilon_{k,l}(\theta)$	weather resistance function
$\mathcal{F}(\theta)$	forecasted wind speed
$va_{\beta,\lambda}$	air speed between nodes N_β, N_λ
${}^l y^k_\lambda$	the time at which U_k arrives at node N_λ, before the disturbance $IS(t^*)$
A	the front-facing area of a UAV
C_D	the aerodynamic drag coefficient
ep	the empty weight of a UAV
D	an air density
b	the width of an UAV
CAP	the energy capacity of an UAV
$vg_{\beta,\lambda}$	ground speed between N_β, N_λ
${}^l y^k_\lambda$	the time at which U_k arrives at node N_λ, before the disturbance $IS(t^*)$ occurrence
${}^l x^k_{\beta,\lambda}$	the binary variable taking the value 1 when U_k is moving between points N_β, N_λ
${}^l c^k_\lambda$	the weight of freight delivered to node N_λ by U_k
Decision Variables:	
$\overline{{}^l x^k_{\beta,\lambda}}$	the binary variable used to indicate if U_k travels between nodes N_β, N_λ, after the disturbance $IS(t^*)$ occurrence
$\overline{{}^l y^k_\lambda}$	the time at which U_k arrives at node N_λ, after the disturbance $IS(t^*)$ occurrence
$\overline{{}^l \pi_k}$	the route of U_k, $\overline{{}^l \pi_k} = (N_{k_1}, \dots, N_{k_i}, N_{k_{i+1}}, \dots, N_{k_\mu})$

The new (replanning) set of sub-missions $\overline{{}^1S}, \dots, \overline{{}^lS}, \dots, \overline{{}^LS}$ guaranteeing timely delivery, are determined by solving the following problem (1):

$$CS\left({}^{\bigcirc}\mathcal{U}, S,\ IS(t^*)\right) = \left((\mathcal{V}, \mathcal{D}), \mathcal{C}({}^{\bigcirc}\mathcal{U}, S,\ IS(t^*))\right), \quad (1)$$

Where:
$\hat{\mathcal{V}} = \left\{\overline{{}^l\Pi}, \overline{{}^lY}, \overline{{}^lC} \mid l = 1 \dots L\right\}$ – the set of decision variables; $\overline{{}^l\Pi}$– is the set of routes; $\overline{{}^lY}$ – is the schedule of the fleet; ${}^{\bigcirc}\mathcal{U}$ - the fleet of UAVs according to rules 1-4 and $\overline{{}^lC}$ – is the sequence of weights of delivered goods by the fleet;
$\mathcal{D}$ – is the set of domains: $\overline{{}^l x^k_{i,j}} \in \{0,1\}$, $\overline{{}^l y^k_\lambda} \in \mathbb{N}$, $\overline{{}^l c^k_i} \in \mathbb{N}$;
$\mathcal{C}$ – is the set of constraints which takes into account the set of routes $\overline{{}^l\Pi}$, schedules $\overline{{}^lY}$ and the disruption $IS(t^*)$ (Radzki et al. 2021). Solving the CSP, however, is very time-consuming, which is a result of the necessity to verify the inequality $\Upsilon_{k,l}(\theta) \geq \mathcal{F}(\theta)$ for each value $\theta \in [0°, 360°)$.
In order to deal with this subject, it was assumed that function $\Upsilon_{k,l}(\theta)$ is approximated by a finite set $\mathbb{Y}_{k,l} = \left\{\Upsilon_{k,l}(\theta_i) \mid i = 1 \dots lq; \theta_i < \theta_{i+1}\right\}$ – see Fig. 3.

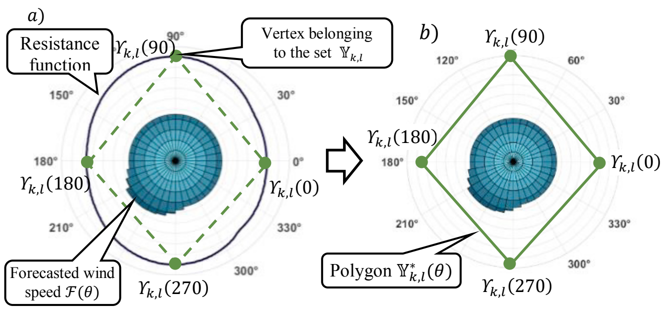


Fig. 3. Discretization of the function $\Upsilon_{k,l}(\theta)$ a) function $\Upsilon_{k,l}(\theta)$, b) polygon $\mathbb{Y}^*_{k,l}(\theta)$

In that context, the following property holds: *For any wind direction* $\theta \in [0°, 360°)$ *function of* $\Upsilon_{k,l}(\theta)$ *mission* $^*S$ *takes values no less than its discrete form* $\mathbb{Y}^*_{k,l}(\theta)$: $\forall \theta \in [0°, 360°)$, $\Upsilon_{k,l}(\theta) \geq \mathbb{Y}^*_{k,l}(\theta)$. In other words $\Upsilon_{k,l}(\theta)$ can be replaced by the set of vertices in $\mathbb{Y}_{k,l}$ reducing the number of vertices, as in the adopted polygon.

6. COMPUTATIONAL EXPERIMENTS

Let us assume that at the time $t^* = 4000$ [s] (see Fig. 2 – proactive plan period) is received information about the delivery time windows (for N_{18} and N_{19}). This disruption implies the necessity of mission replanning (see Fig. 2 – rescheduling period). Implementation of proposed CSP (1) (IBM ILOG enviroment) has shown that the solution can be obtained in time which does not exceed 35 s. Fig. 2 (dashed lines of the reactive plan period), shows the plan of a mission adapted to the disruption. The first rule was used in assigning mission$^*S$, i.e., *If the mission S is not robust to disruption* $IS(t^*)$ *then it should be checked whether it is possible to adapt, adjusting it to new conditions.* In the case under consideration, none of the UAVs were turned back.

Table 2. Results of the computational experiments

		NS	$\mathcal{F}(\theta) = 11\frac{m}{s}$ $\forall\theta \in [0°, 360°)$		NS	$\mathcal{F}(\theta) = 12\frac{m}{s}$ $\forall\theta \in [0°, 360°)$		NS	$\mathcal{F}(\theta) = 13\frac{m}{s}$ $\forall\theta \in [0°, 360°)$	
n	K		TCR [s]	TC [s]		TCR [s]	TC [s]		TCR [s]	TC [s]
40	2	7	18,76	1373,4	7	35,71	2534,7	7	27,69	2091,3
	3	6	154,16	t>600	6	147,46	t>600	7	541,51	t>600
	4	5	408,95	t>600	5	442,02	t>600	5	698,24	t>600
60	2	12	309,44	t>600	12	66,42	t>600	12	67,94	t>600
	3	11	334,01	t>600	×	t>600	t>600	9	236,8	t>600
	4	×	t>600	t>600	×	t>600	t>600	×	t>600	t>600
70	2	13	411,58	t>600	13	139,59	t>600	14	153,53	t>600
	3	12	756,58	t>600	×	t>600	t>600	×	t>600	t>600
	4	×	t>600	t>600	×	t>600	t>600	×	t>600	t>600
80	2	16	360,98	t>600	15	175,65	t>600	16	502,24	t>600
	3	×	t>600	t>600	×	t>600	t>600	×	t>600	t>600
	4	×	t>600	t>600	×	t>600	t>600	×	t>600	t>600

n – number of delivery points; K – size of fleet; TRC – time of computation with relaxation; TC – time of computation without relaxation; × – no solution allowed in time $t < 600s$; NS - number of sub-missions

The received mission was resistant to the given weather conditions (9 m/s) and guaranteed timely delivery of the expected goods (also for N_{18} and N_{19}). In order to assess the scalability of the proposed approach (in an online mode i.e., <600 s), the series of quantitative experiments have been carried out. Table 2 presents the obtained results (the three functions of forecasted weather $\mathcal{F}(\theta) = 9, 10, 11\, m/s$ have been considered).
For each instance of network ($n = 40,60,70,80$ and $K = 2,3,4$), a proactive mission plan was set out. It was assumed that at the moment $t^* = 2000$ [s] there was a change in delivery time window. Results (i.e with relaxation TCR and without relaxation TC) are presented in Table 1. The experiments show that, the mission can be effectively refined, (taking into account specific types of disruptions) for networks of a size up to 80 delivery points, and 2 UAVs. Such results were achieved through the above mentioned relaxation.

7. CONCLUSIONS

This study presents a method and procedure for the multiple autonomous vehicles mission flight planning in dynamic environment including changing weather as well as changes in the volume and delivery times. The approach proposed is heuristic in nature, but highly scalable, robust, and simple to implement. The heuristic nature of the approach results from the implementation of arbitrarily adopted condition-action rules used in the process of planning acceptable end-to-end routes guaranteeing the return of UAVs to the base (depot) before the battery run outs. Heuristic rules used are implemented in the CP framework allowing fast calculation of robustness function assessing the fleet resistance to changes in the orders of impatient customers. A quick assessment of the resilience of the fleet follows from implementation of the condition guaranteeing convexity of robustness function. Development of this condition provides main contribution resulting in proposed method for proactive-reactive UAVs fleet mission planning.

Thanks to this the proposed approach is heuristic in nature, offering open structure modelling framework being highly scalable, robust, and simple to implement. Although CP based approach gives the exact solution, it is useful only for very small instances due to the NP-hardness of the problem. The conducted experiments show that using a personal computer in online mode the scale of the cases under consideration includes networks not exceeding 80 points operated by a maximum of 2 UAVs. This limitation is a challenge for future work aimed at implementation of meta- heuristic approaches, particularly the genetic algorithms, enabling to cope with problems of a much large scale.

Future research will include evaluation of environment dynamics and UAV failures while taking into account the uncertain nature of the real-world variables. This means the need to extend the existing model with elements of fuzzy logic and in particular the ordered fuzzy numbers formalism (Rudnik and Walaszek-Babiszewska 2012).

In future work, we plan also to study the case of multi-depot and multiple UAVs (both homogeneous and heterogeneous) in the context of trade-off between the size of used UAVs fleet and the degree of implementation of planned deliveries. The inclusion of the range/endurance of the UAVs as a shared variable in such more challenging scenario will further enhance the richness of the problem.

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