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REGULAR PAPER

Modelling Robust Delivery Scenarios for a Fleet of Unmanned Aerial Vehicles in Disaster Relief Missions

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Abstract
Besides commercial and military applications, unmanned aerial vehicles (UAVs) are now used more commonly in disaster relief operations. This study proposes a novel model for proactive and reactive planning (different scenarios) that allow for a higher degree of realism, thus a higher likelihood for a mission of being executed according to the plan even when weather forecasts are changing. The novelty of this study results from the addition of a function of resistance of UAVs mission to changes in weather conditions. We link the influence of weather conditions on the UAV's energy consumption. The goal is to ensure the completion of planned deliveries by a fleet of UAVs under changing weather conditions before their batteries discharge and to identify the emergency route for returned if the mission cannot be completed. An approach based on constraint programming is proposed, as it has proven to be effective in various contexts, especially related to the nonlinearity of the system's characteristics. The proposed approach has been tested on several instances, which have allowed for analyzing how the plan of mission is robust to the changing weather conditions with different parameters, such as the fleet size, battery capacity, and distribution network layout.

Keywords Unmanned aerial vehicles routing · Unmanned aerial vehicles scheduling · Re-routing · Rescheduling · UAV fleet mission planning · Robust planning

1 Introduction

The unmanned aerial vehicles (UAVs) are used for the purpose of disaster relief in three application domains: aerial monitoring for damage's evaluation, logistics and cargo delivery, and post disaster aerial assessment [1]. Besides natural disasters, such as earthquakes, landslides, avalanches and tornadoes, flooding poses the most immediate impact to personal safety. In that context, deliveries of essential goods, such as medical supplies, food and water, within the first couple of hours are crucial [2–5]. Therefore, expectations related to the organization of appropriate logistics support, indicate that a tool is needed to support the planning of rescue missions for UAV fleets. Planning of UAV missions extends the well-known Vehicle Routing Problem, which belongs to the class of NP-hard (nondeterministic polynomial-hard) problems, by adding the complexity of three-dimensional space [6, 7]. Vehicle routing in the context of relief operations, differs significantly from commercial routing problems, where the primary goal is to minimize costs [8]. The routing decisions should ensure prompt and sufficient distribution of essential goods to all aid recipients. Decision making is performed in a highly volatile and dynamic environment. Planning and routing of a disaster relief mission should take into consideration typical conditions, such as [9]:

- Small number of destinations per trip.
- Damages in infrastructure.
- Delays in fulfilment of the requirements may increase the receiver's distress.

Categories (1), (3), (8)

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Moreover, plans of UAV missions must consider constraints resulting from a UAV's characteristics (such as: maximum payload, energy capacity, physical dimensions, etc.) and weather conditions (wind speed and wind direction) [10].

A research gap exists with regard to the planning of UAV missions in a manner, which is robust the changing weather conditions. Our work is application-oriented and it extends the previous works of Thibbotuwawa et al. [11, 12], and Radzki et al. [13], as we use declarative modelling methods in order to provide alternative scenarios for disaster relief operations. In our previous works we have proposed:

In our previous works we have proposed:

- Declarative modelling framework for an iterative approach to planning of UAV missions in the environment with constant weather conditions [11],
- knapsack driven proactive UAVs mission planning [13],by using a model that takes into account the change of the cargo's weight during the flight,
- Fast prototyping of feasible UAVs fleet scenarios with different weather conditions (wind speed and direction), different flight strategies (with constant air speed or constant ground speed), variable fleet sizes and number of recipients [12].

This study considers the mission planning of a UAV fleet under the assumption of an emergency return route (reactively activated when the weather conditions change beyond the expected range), and provides new contributions to the currently available literature. The novelty of the presented approach results from the extension of the declarative model used in our previous works, particularly in [11–13], by the addition of a function of resistance of a UAV mission to changes in the weather conditions. The proposed approach allows for foreseeing the UAV's battery discharged before completing its mission and thus, can be used in the process of reactive planning of UAVs fleet mission.

Proposed model supports the decision-makers in the search for a plan of missions (with routes and flight schedules) which allows for delivering of the expected quantity of goods to a specific group of recipients. We consider uncertain weather conditions during a mission, such as wind direction, and speed. The goal is to find a robust ("weatherproof") plan of mission, which ensures that batteries of UAVs shall not discharge before completing the mission.

The main contributions of this paper are summarized, as follows:

1) The proposed model takes into consideration several factors, which influence the ability of UAVs to successfully complete missions, such as: changing weather conditions, different energy consumption by UAVs, changes in UAV weight when operating routes, an emergency return to the base before completing a mission. Moreover, collision avoidance is taken into consideration. Therefore, the alternative scenarios UAV fleet missions can be elaborated, which are more realistic.
2) The declarative modelling driven approach is formulated for the assessment of alternative UAV fleet's routing and scheduling scenarios. Proposed model allows for predictive (i.e. taking into account changes in the forecasted weather conditions) and reactive (i.e. enabling interruption of a UAV mission) planning in terms of the Constraint Satisfaction Problem.
3) The proposed approach replaces traditionally implemented computer simulation methods enabling offline planning of UAVs missions, with a constraint programming environment enabling online planning, e.g., IBM ILOG.

The remainder of the paper is structured as follows: related works are discussed in Sec. 2. A case study is introduced in Sec. 3. A model for routing and scheduling of missions for a fleet of UAVs is presented in Sec. 4. The method for planning of different scenarios for relief missions based on the Constraint Satisfaction Problem is described in Sec. 5. Computational experiments are presented in Sec. 6. Final conclusions are stated in Sec. 7, followed by a description of future research.

2 Literature Review

A considerable amount of studies has been devoted to the application of UAVs in emergency situations in which they are used for transport of much-needed water, food, and medical supplies over hazardous (flooded) terrain [7]. It confirms that an interest among academics in UAV-Assisted Disaster Management is increasing [14]. In particular, there is a need to search for scenario-driven planning methods that aim at preparation of plans for missions of UAVs, and that allow for determining whom to serve, how much to deliver, and which routes to travel. There is need for interactive tools that facilitate analyzing and comparing different scenarios for UAV fleets, as well as an iterative identification of sound and efficient mitigation strategies [15].

Previous related studies cover a very wide range of issues, such as:

- UAVs' fleet planning and scheduling [16].
- Optimization with various criteria e.g.: fuel consumption [17], delivery time [7] and delivery costs [18].
- Various fields of application e.g., reconnaissance and mapping [19], package delivery [20] and delivery communication capabilities [14, 21].

Planning of UAV missions may take into account different variants of objective functions such as, reducing individual UAV costs, increasing safety in operations, reducing lead time and increasing load capacity of the entire system [22–24]. Several authors have analyzed a possibility of using drones in civil (e.g. urban environment [25]), and military (e.g., the battlefield) applications [26].

One of the more commonly used mathematical representation for planning and scheduling of drone missions is Mixed Integer Programming and Mixed Integer Linear Programming [27–29]. Due to the NP-difficult nature of problems and occurrence of non-linear constraints, machine learning and/or artificial intelligent methods are used i.e., metaheuristics driven, like Variable Neighbourhood Search and Tabu Search [29, 30]. Recent publications also present the declarative modelling based models, which enable for constraint programming problem formulation [10, 11, 13, 31, 32]. The above-mentioned formal methods are supplemented by simulation tools, such as flight simulators [33, 34].

A relatively few works are devoted to the planning of UAV fleet missions taking into account various technical and environmental factors influencing possible solutions [10, 35]. Among the listed factors, significant are:

- Technical parameters of UAVs (UAV dimensions, battery capacity and carrying payload limits) [36].
- Changing weather conditions (the wind speed, wind direction, wind gust, precipitation, icing, turbulences and air density and temperature) [7, 36].
- Dynamically changing terms of delivery and static or moving obstacles (withdrawing or changing the date and place of deliveries as well as their volume, collisions avoidance) [37].

The characteristics of UAV greatly affect the energy consumption. The current literature presents primarily linear approximations of energy consumption [12], which makes realistic planning difficult.

In the literature, weather conditions are mainly addressed in relation to control of trajectory of UAVs mission. In the current studies, Kazim et al. [38] propose a fully nonlinear robust adaptive controller for tracking the trajectory of UAVs in the presence of realistic wind gusts. In related work [39], a self-calibrated UAV control framework is proposed to compensate the changing wind conditions without operator intervention or manual tuning. A similar approach is proposed in [40]. There, the algorithm estimates and compensates uncertainties to maintain UAV flight with disturbance generated by wind gusts. However, the work on the UAV trajectory control in changing weather conditions might be complementary to this paper, but they don't provide a relevant solution that may be implemented for alternative scenarios of mission planning.

The indicated research gap has become inspiration for conducting this research.

The reactive strategies play a pivotal role in disaster relief mission, as they are linking the "route discovery" (route planning), and "route maintenance" (reaction for mission interruption) concepts [41]. This study proposes a novel declarative model for proactive and reactive planning (different scenarios) that allow for a higher degree of realism, thus a higher likelihood for a mission of being executed according to the plan even when weather forecasts are changing.

3 A Case Study

Planning of a relief mission is challenging especially for the last mile operations (from distribution center to the recipients) due to limited resources and other constraints [42].

Besiou et al. [43] have identified a need for "empirically-grounded analytical modeling papers" in the domain of disaster relief operations research. In order to illustrate an essence of the problem, we consider a situation of the distribution of basic necessities (clothing, medicines, dressings, and food during) in flood relief operations. Figure 1 (and Table 1) presents the map of floodplains (352 km2) for the surrounding areas of Wolinia (north Poland, Pomeranian Region: 54°36′56″N 17°32′20″E). In order to ensure the safety of inhabitants of the flooded area, there are designated collection points (referred here also as pickup points) for deliveries $N_2 - N_{11}$ (see Fig. 1). Essential goods are delivered by a Volunteer Fire Brigade (VFB) unit, which is stationed in Wolinia during the flood (N_1 – Fig. 1). The number of essential goods stored in N_1 is determined by the number of recipients at a given collection point ($N_2 - N_{11}$). They are respectively: $z_2 = 5$ [kg], $z_3 = 5$ [kg], $z_4 = 5$ [kg], $z_5 = 5$ [kg], $z_6 = 5$ [kg],$z_7 = 10$ [kg],$z_8 = 1$ 5 [kg],$z_9 = 15$ [kg],$z_{10} = 5$ [kg], $z_{11} = 5$ [kg].

It is assumed that the transport of items in such a defined distribution network G is performed by the fleet of three UAVs: $\mathcal{U} = \{U_1, U_2, U_3\}$ owned by VFB in Wolinia.

Technical parameters of the UAVs are presented in Table 2. All UAVs are available at zero time. Times of delivery depend on the sequence of customers to be served along flight routes. Breakdown and maintenance times and costs are not considered.

In disaster relief operations a prompt response and an equitable distribution of aid among recipients are crucial [44]. In modelling of a mission's plan, the emphasis should be placed on a dynamic approach to scheduling and routing of vehicles (and their tracking) whilst ensuring robustness to changing conditions [45].

To meet the above mentioned postulates, it is assumed here that essential goods should be delivered within 45 min from receiving an order ($t_{max} = 2700$ [s]). A delivery takes place in different weather conditions, i.e., the wind speed forecast is

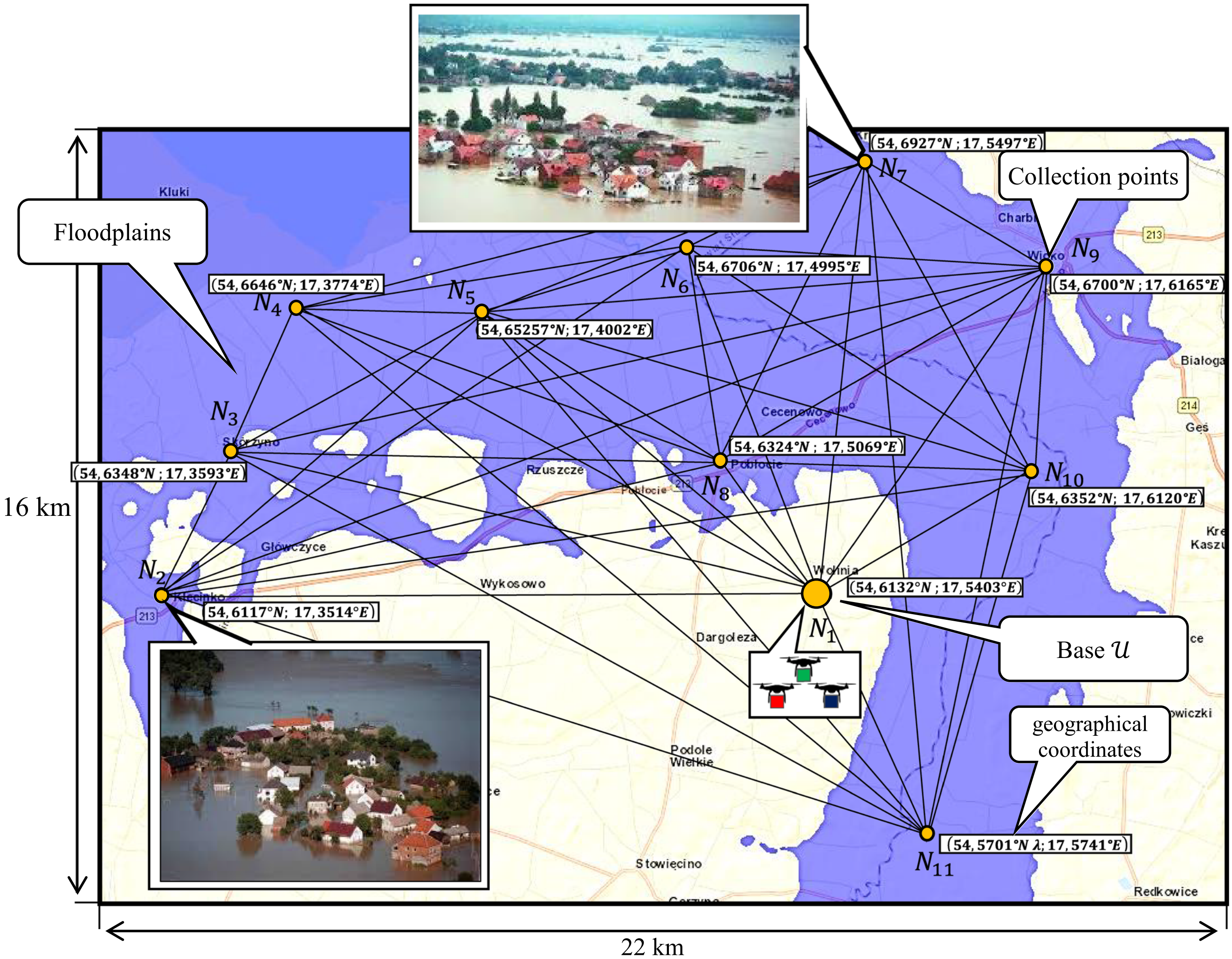

Fig. 1 The area of the floodplain with the distribution network$G$, (own study based on: https://www.floodmap.net/?ll=54.646227,17.545076&z=12&e=22 and https://dziennikzachodni.pl/wiosna-dopadnie-nas-powodz-stulecia-zobacz-mape/ga/216213/zd/478064)

Table 1 Travel distances between the nodes [km]

$d_{i,j}$	N_1	N_2	N_3	N_4	N_5	N_6	N_7	N_8	N_9	N_{10}	N_{11}
N_1	0	12,8	12,2	11,8	10,0	6,9	9,2	3,0	7,9	5,0	5,9
N_2	12,8	0	1,3	2,9	4,5	10,6	14,6	10,3	17,5	16,8	17,9
N_3	12,2	1,3	0	1,6	3,2	9,4	13,3	9,5	16,4	15,9	17,5
N_4	11,8	2,9	1,6	0	2,0	8,2	12,0	9,0	15,4	15,2	17,3
N_5	10,0	4,5	3,2	2,0	0	6,2	10,1	7,1	13,4	13,2	15,7
N_6	6,9	10,6	9,4	8,2	6,2	0	4,2	4,4	7,2	7,9	12,7
N_7	9,2	14,6	13,3	12,0	10,1	4,2	0	7,7	4,9	7,7	14,1
N_8	3,0	10,3	9,5	9,0	7,1	4,4	7,7	0	8,1	6,5	8,9
N_9	7,9	17,5	16,4	15,4	13,4	7,2	4,9	8,1	0	3,9	11,0
N_{10}	5,0	16,8	15,9	15,2	13,2	7,9	7,7	6,5	3,9	0	7,0
N_{11}	5,9	17,9	17,5	17,3	15,7	12,7	14,1	8,9	11,0	7,0	0

known vw and wind's direction θ. In the analysed case, a south wind is forecasted ($\theta = 80°$) with a speed not exceeding $vw = 10\frac{m}{s}$. For the presented weather conditions, a research question is stated, as follows:

Is an available fleet $\mathcal{U}$ able to ensure the deliveries of the required quantity of goods $\{z_2, \ldots.., z_{11}\}$, to the collection

Table 2 Technical parameters of UAVs

Technical parameters of UAVs	Value	Unit
Payload Capacity (Q)	25	kg
Battery capacity (CAP)	7500	kJ
Airspeed (va)	20	m/s
Drag coefficient (C_D)	0.54	-
Front surface of UAV (A)	1.2	m^2
UAV width (b)	8.7	m

> points $\{N_2, ..., N_{11}\}$, in a given time horizon (t_{max}) and for the forecasted weather conditions (vw, θ)?

In this disaster relief mission, a proactive mission plan S is sought (including routes and UAVs' flight schedules), that ensures the delivery of the expected number of items, in the given weather conditions ($\theta = 80^\circ, vw \leq 10\frac{m}{s}$) and in the defined time (45 min.).

An example of such plan is presented in Fig. 2a. Routes of the UAVs $\pi_1 = (N_1, N_2, N_3, N_4, N_5, N_8, N_1)$, $\pi_2 = (N_1, N_{11}, N_{10}, N_9, N_1)$ $\pi_3 = (N_1, N_7, N_6, N_8, N_1)$ enable to deliver the required goods at the given collection points, while not exceeding the minimum battery level of each UAV. Total energy consumption results from the consumption during the transportation of the articles of a certain weight (z_i) and the energy consumption associated with customizing airspeed of the UAV (va) to weather conditions (flying counter wind and with the wind). They are calculated, as 90.3 %, 93.7 %, 79.1 % of the battery capacity CAP=7500 kJ. In the presented solution it is assumed that drones move with a constant ground speed $vg = 20\frac{m}{s}$. Adoption of a constant ground speed ensures a timely delivery of goods regardless of the weather conditions ($\theta = 80^\circ, vw \leq 10\frac{m}{s}$). However, that assumption results in significant energy consumption, because airspeed va needs to be adjusted in accordance with the existing weather conditions [12].

In the second scenario (Fig. 2b), the initial plan of mission (from Fig. 2a) is executed in different weather conditions (e.g., in a north-west wind $\theta^{'} = 150^\circ$). In such case, the initially acceptable (for $\theta = 80^\circ$) energy consumption U_1 has been excelled. The energy consumption for the new case is respectively: 106.4 %, 82.5 and 69.7 %. It means that the presumed change in weather makes it impossible to finish the flight by one of the UAVs. The mission U_1 would finish earlier between nodes N_8 and N_1 (due to the lack of fuel/empty battery – see Fig. 2b). This means that a change in weather conditions significantly affects the success of the planned mission, and consequently leads to the following question:

> Does a delivery plan exist which is robust to the assumed changing weather conditions for a given fleet of UAVs performing deliveries in a defined distribution network (routes and corresponding delivery schedules)?

In order to answer this question, firstly, robustness of a mission plan S to weather conditions must be defined. It is assumed that the weather conditions prevailing during the mission S are described by the pair$(\theta, vw) \in \mathbb{Z}$. Where $\mathbb{Z}$ is a set of forecasted weather conditions that may occur during a mission:$\mathbb{Z} = \{(\theta, vw) | \theta \in [0^\circ, 360^\circ), vw \leq Z(\theta)\}$. Set $\mathbb{Z}$ is determined by the function $Z(\theta)$ where: $\theta \in [0^\circ, 360^\circ)$ determines the maximum forecasted wind speed for a given wind directionθ. It is assumed that the function $Z(\theta)$ is known and determined on the basis of available weather forecasts. Examples of two weather conditions are shown in Fig. 2a $\left(80^\circ; 10\frac{m}{s}\right)$ and 2b $\left(150^\circ; 10\frac{m}{s}\right)$.

The considered weather conditions (including 16 different wind directions), are shown respectively in Fig. 3a and b. Area limited by the graph of function $Z(\theta)$ contains points corresponding to the weather conditions that may occur during a mission – set $\mathbb{Z}$.

The function $\Upsilon_{\mathcal{USG}}$: $\Phi \rightarrow UW$ (where: $\Phi = [0^\circ, 360^\circ)$ is a set of directions θ, and $UW \subset \mathbb{R}_+^0 = \{a | a \in \mathbb{R} \wedge a \geq 0\}$ is a set of wind speedsvw) that represents the maximum wind speed $\Upsilon_{\mathcal{USG}}(\theta) = vw$ (for a given direction θ) at which a mission S can be completed. It is worth noting that usually an inequality occurs:$\Upsilon_{\mathcal{USG}}(\theta) \geq Z(\theta)$. The function $\Upsilon_{\mathcal{USG}}(\theta)$ determines the boundary weather conditions (speed vw for a given direction θ), so when they would be exceeded then a battery of at least one UAV from the fleet $\mathcal{U}$ shall be empty.

It is assumed that function $\Upsilon_{\mathcal{USG}}(\theta)$ is determined for a feasible plan of mission S, as the maximum value of set $\Gamma(\theta) \subseteq UW$ that contains relevant wind speed's values vw, for a given direction θ:

$$\Upsilon_{\mathcal{USG}}(\theta) = \max \Gamma(\theta) \tag{1}$$

Where: $\Gamma(\theta) \subseteq UW$ – a set of wind speed's values vw, which for a direction θ ensures the successful completion of a plan of missions S by a fleet $\mathcal{U}$ in a distribution network G.

Function $\Upsilon_{\mathcal{USG}}(\theta)$ determines a set of weather conditions $\mathbb{Y}_{\mathcal{USG}} = \{(\theta, vw) | \theta \in [0^\circ, 360^\circ), vw \leq \Upsilon_{\mathcal{USG}}(\theta)\}$ which ensures a successful completion of a plan of mission S by a fleet $\mathcal{U}$ in a distribution network G. Therefore, it enables for the definition of a robust plan for a mission S.

Definition A plan of mission for a fleet in a distribution network is robust to weather conditions only if, all UAVs from a fleet return to the base after all deliveries are made.

According to the above definition, a robust plan of mission is such a plan which implementation is possible for all forecasted weather conditions $(\theta, vw) \in \mathbb{Z} \subseteq \mathbb{Y}_{\mathcal{USG}}$. Fig. 4 presents the graph of function $\Upsilon_{\mathcal{USG}}(\theta)$, which is designated (in accordance with (1)) for UAV's routes that are performed during the mission from Fig. 2. The area limited by a graph of function $\Upsilon_{\mathcal{USG}}(\theta)$ contains points, which correspond to the weather conditions that ensure completion of a plan of mission S – set $\mathbb{Y}_{\mathcal{USG}}$. In this chart also, two points are distinguished for the forecasted weather conditions: $\mathbb{Z} = \left\{\left(80^\circ; 10\frac{m}{s}\right); \left(150^\circ; 10\frac{m}{s}\right)\right\}$.

In the first case, the highlighted point is located inside the $\mathbb{Y}_{\mathcal{USG}}$, while in the second case, it is not. It means that in the first case, the wind speed vw is lower than the allowed maximum value: vw - thus the mission S is accomplished, as UAV's batteries are not discharged. In the second case, a wind

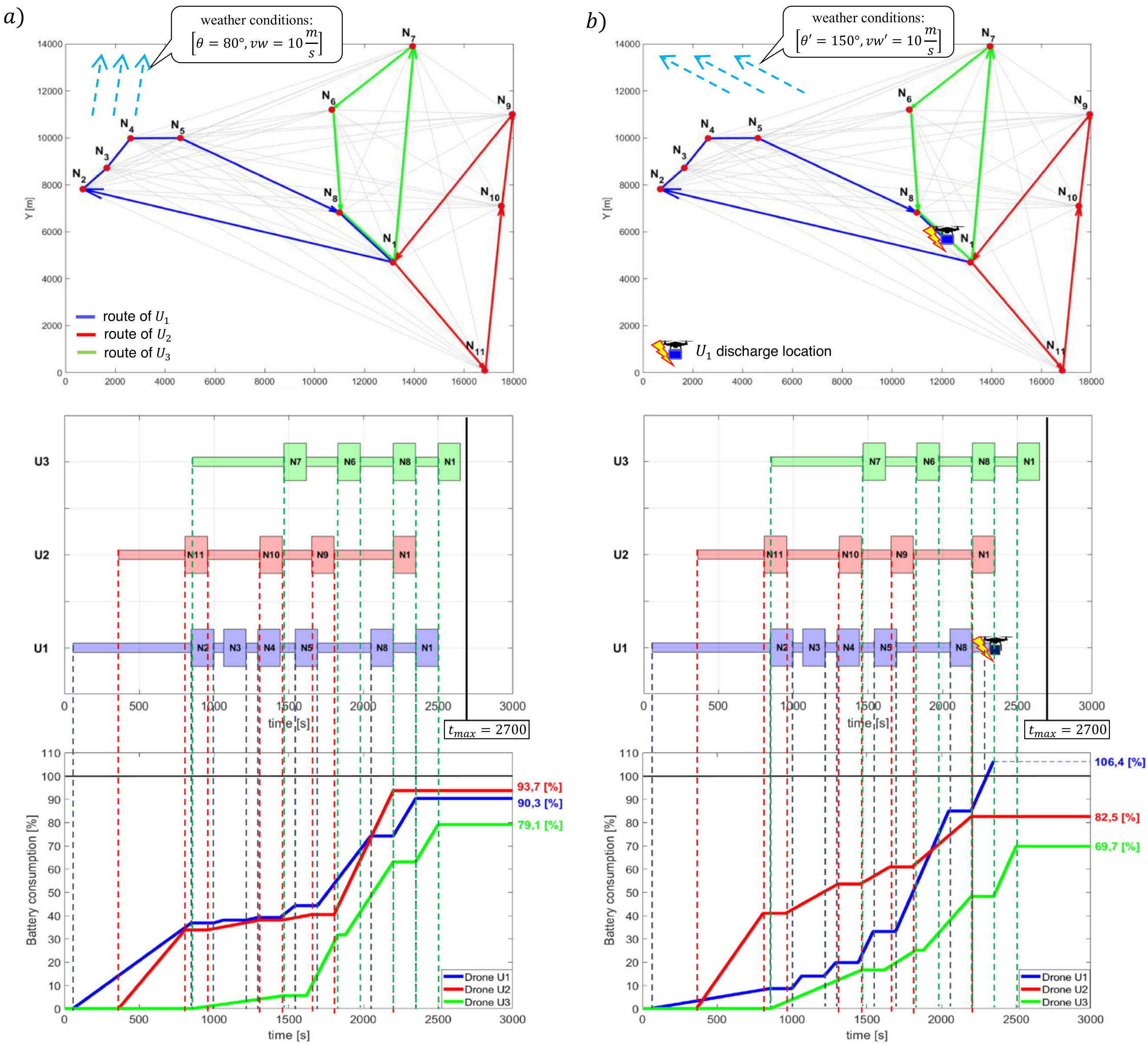

Fig. 2 Plans of UAVs fleet missions specified by routings, delivery flow charts and energy consumption time diagrams under different wind directions: (**a**) vw = 10 m/s, θ = 80° (**b**) vw =10 m/s, θ =150°

speed exceeds the permissible value: $vw' > \Upsilon_{\mathcal{USG}}(150)$ which means that during this mission a battery of at least one of the UAVs would be discharged. Due to the fact that not all elements of the set $\mathbb{Z}$ belong to the set $\mathbb{Y}_{\mathcal{USG}}$, the plan of mission S from Fig. 2 is not robust to the weather conditions. Thus, there is a risk that not all essential goods would be delivered.

The search for a plan of mission S, that is robust to given weather conditions requires determining a plan (including routes of individual UAVs), that shall ensure its successful execution for both weather conditions. Therefore, a plan of mission S is sought, which function $\Upsilon_{\mathcal{USG}}(\theta)$ meets both conditions simultaneously: $\Upsilon_{\mathcal{USG}}(150) > vw'$ and $\Upsilon_{\mathcal{USG}}(80) > \mathrm{vw}$.

In Fig. 5, a search for a proactive plan of mission is presented, that shall be robust enough to the given changes in weather conditions. A set of forecast weather conditions $\mathbb{Z}$ is given, for a fleet $\mathcal{U}$ and a distribution network G. A searched plan of mission S (routes and related flight schedules) for a fleet $\mathcal{U}$, shall ensure a timely delivery (within a given time *a*)

Forecasted weather conditions			θ	$Z(\theta)$
Wind direction		Wind speed		
E	east	0 … 8	0°	8
ENE	east northeast	0 … 8.5	22°30'	8.5
NE	northeast	0 … 9	45°	9
NNE	north northeast	0 … 9	67°30'	9
N	north	0 … 9	90°	9
NNW	north northwest	0 … 9.5	112°30'	9.5
NW	northwest	0 … 10	135°	10
WNW	west northwest	0 … 10	157°30'	10
W	west	0 … 10	180°	10
WSW	west southwest	0 … 9.5	202°30'	9.5
SW	soutwest	0 … 9	225°	9
SSW	south southwest	0 … 9	247°30'	9
S	south	0 … 9	270°	9
SSE	south southeast	0 … 8.5	292°30'	8.5
SE	southeast	0 … 8	315°	8
ESE	east southeast	0 … 8	337°30'	8

b)

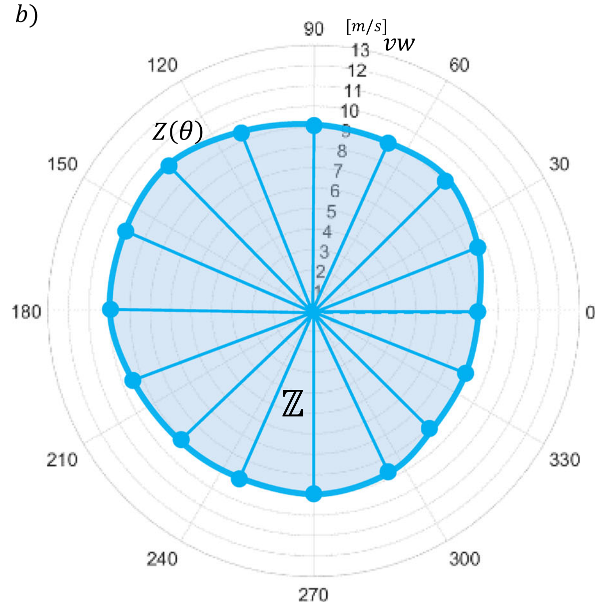

Fig. 3 (**a**) A sample weather forecast (**b**) and a corresponding function $Z(\theta)$

horizon) to all recipients in a G network, and shall be robust to forecasted weather conditions $\mathbb{Z}$. Thus, a plan of mission S shall meet conditions $\mathbb{Z} \subseteq \mathbb{Y}_{\mathcal{USG}}$ that: $\forall_{\theta\in[0^\circ,360^\circ)} \Upsilon_{\mathcal{USG}}(\theta) \geq Z(\theta)$.

Planning of a UAV mission, that is robust to the given weather conditions belongs to the combinatorial optimization problems in the class of synthesis problems. These types of problems are NP-hard. A search for a robust UAV fleet's mission can be modeled using the Constraint Satisfaction Problem (CSP) formalism (which allows taking into account non-linear constraints of the energy consumption). That allows for implementing the proposed model directly in commercially available constraint programming environments, such as IBM ILOG CPLEX, Gurobi, ECL^{i}PS^e, Oz Mozart (and others).

4 The Model for Planning of UAVs' Mission

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

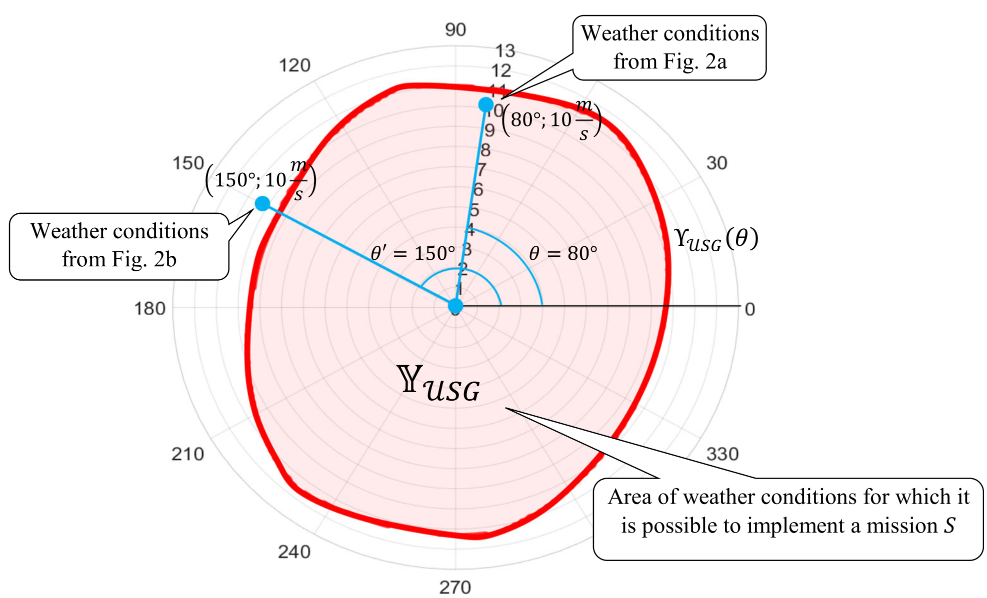

Fig. 4 Robustness $\Upsilon_{\mathcal{USG}}(\theta)$ for mission S from Fig. 2

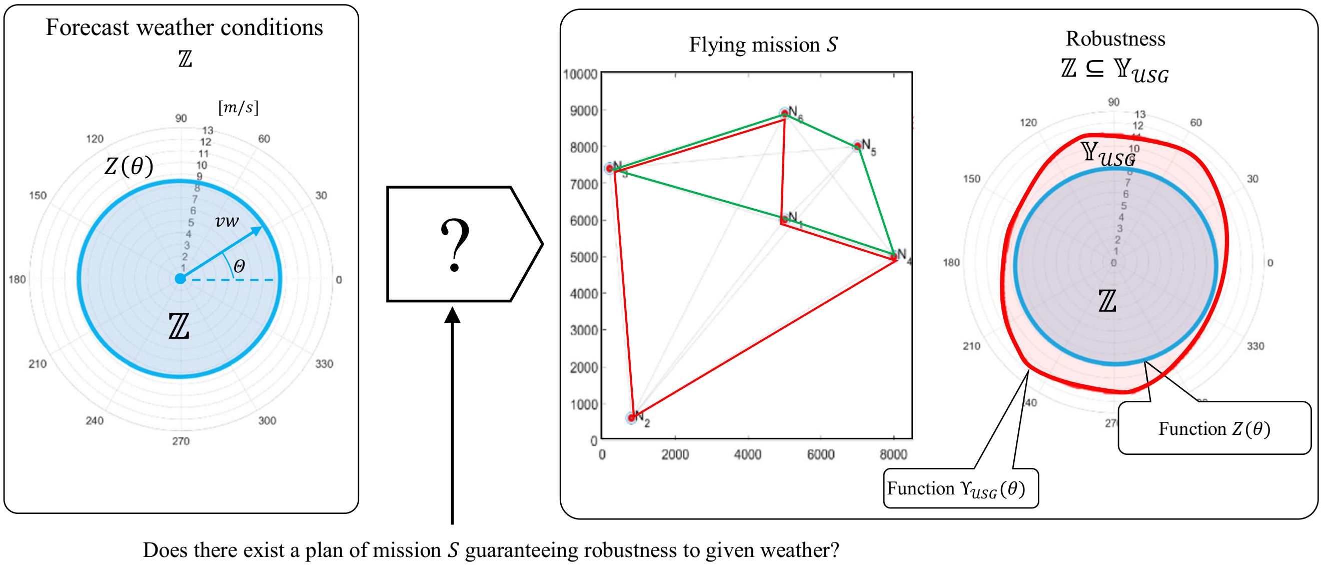

Fig. 5 Illustration of UAVs fleet robust mission planning

Parameters

Network

G graph of a distribution network: $G = (N, E)$ where $N = \{1 \ldots n\}$ is a set of nodes ($n = |N|$), $E = \{\{i, j\} | \ i, j \in N, \ i \neq j\}$ 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

pn_i position of node i in geographical coordinates: $pn_i = (\phi_i, \lambda_i)$, where ϕ_i - latitude of node i, λ_i – longitude of node i

CSL Customer's Satisfaction Level expressed, as a % of the amount of delivered goods ordered by customers

UAV Parameters

$\mathcal{U}$ set (fleet) of UAVs: $U = \{U_1, ..., U_k, ..., U_K\}$ where U_k is a k-th UAV

K size of the fleet of UAVs

Υ_{USG} $\mathcal{U}$ fleet resistance to changes in weather conditions during the execution of the plan of mission S in distribution network G

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

g gravitational acceleration

b width of a UAV

CAP maximum energy capacity of a UAV

Environmental Parameters

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

$Z(\theta)$ function determining the upper value of wind speed for wind direction θ

$va_{i,j}$ airspeed of a UAV traveling from node i to node 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 node j

Decision Variables.

$x^k_{i,j}$ binary variable used to indicate if U_k travels from node i to node j $x^k_{i,j} =$
$$\begin{cases} 1 & \text{if } U_k \text{ travels from node } i \text{ to node } j \\ 0 & \text{otherwise.} \end{cases}$$

y^k_i time at which U_k arrives at node i

c^k_i weight of freight delivered to node i by U_k

$f^k_{i,j}$ weight of freight carried from node i to node j by U_k

$P^k_{i,j}$ energy per unit of time, consumed by U_k during a flight from node i to node j

bat^k total energy consumed by U_k

s^k take-off time of U_k

cp_i total weight of freight delivered to node i

π_k route of U_k $\pi_k = (v_1, \ldots, v_i, v_{i+1}, \ldots, v_\mu)$, $v_i \in N$, $x^k_{v_i,v_{i+1}} = 1$

Auxiliary Variables

cs^k total weight of freight transported by U_k
fc_i^k weight of freight transported by U_k at the moment of arrival to node i

Sets

Y^k set of times y_i^k, schedule of U_k UAV
Y family of Y^k, schedule of fleet $\mathcal{U}$
C^k set of c_i^k, payload weight delivered by U_k UAV
C family of C^k
Π set of UAV routes π_k
S plan of mission: $S = (\Pi, Y, C)$

Constraints

Routes. Relationships between the variables describing drone take-off times/mission start times and task order:

$$s^k \geq 0; k = 1, ..., K \quad (2)$$

$$y_i^k \geq 0; i = 1, ..., n; k = 1, ..., K \quad (3)$$

$$(|s^k - s^q| \geq ts); k, q = 1, ..., K; \quad k \neq q \quad (4)$$

$$\sum\nolimits_{j=1}^{n} x_{1,j}^k = 1; k = 1, ..., K \quad (5)$$

$$(y_i^k \neq 0 \wedge y_i^q \neq 0) \Rightarrow (|y_i^k - y_i^q| \geq w); i = 1, ..., n; k, q = 1, ..., K; \quad k \neq q \quad (6)$$

$$\left(x_{1,j}^k = 1\right) \Rightarrow \left(y_j^k = s^k + t_{1,j}\right); j = 1, ..., n; k = 1, ..., K \quad (7)$$

$$\left(x_{i,j}^k = 1\right) \Rightarrow \left(y_j^k = y_i^k + t_{i,j} + w\right); j = 1, ..., n; i = 2, ..., n; k = 1, ..., K \quad (8)$$

$$\sum\nolimits_{j=1}^{n} x_{i,j}^k = \sum\nolimits_{j=1}^{n} x_{j,i}^k; i = 1, ..., n; k = 1, ..., K, \quad (9)$$

$$y_i^k \leq t_{max} \times \sum\nolimits_{j=1}^{n} x_{i,j}^k, i = 1, ..., n; k = 1, ..., K, \quad (10)$$

$$x_{i,i}^k = 0; i = 1, ..., n; k = 1, ..., K \quad (11)$$

.

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

$$c_i^k \geq 0; i = 1, .., n; k = 1, ..., K \quad (12)$$

$$c_i^k \leq Q \times \sum\nolimits_{j=1}^{n} x_{i,j}^k; i = 1, ..., n; k = 1, ..., K \quad (13)$$

$$\sum\nolimits_{i=1}^{n} c_i^k \leq Q; k = 1, ..., K \quad (14)$$

$$\left(x_{i,j}^k = 1\right) \Rightarrow c_j^k \geq 1; k = 1, ..., K; i = 1, ..., n; j = 2n \quad (15)$$

$$\sum\nolimits_{k=1}^{K} c_i^k = cp_i; i = 1, ..., n \quad (16)$$

$$cp_i \leq z_i; i = 1, ..., n \quad (17)$$

$$\sum\nolimits_{i=1}^{n} c_i^k = cs^k; k = 1, ..., K \quad (18)$$

$$\left(x_{1,j}^k = 1\right) \Rightarrow \left(fc_j^k = cs^k\right); j = 1, ..., n; k = 1, ..., K \quad (19)$$

$$\left(x_{i,j}^k = 1\right) \Rightarrow \left(fc_j^k = fc_i^k - c_i^k\right); i, j = 1, ..., n; k = 1, ..., K \quad (20)$$

$$\left(x_{1,j}^k = 1\right) \Rightarrow \left(f_{1,j}^k = cs^k\right); j = 1, ..., n; k = 1, ..., K \quad (21)$$

$$\left(x_{i,j}^k = 1\right) \Rightarrow \left(f_{i,j}^k = fc_j^k\right); i, j = 1, ..., n; k = 1, ..., K \quad (22)$$

Energy consumption. The plan of mission S is robust to weather conditions $Z(\theta)$. That means that an amount of energy needed to complete tasks performed by any UAV cannot exceed the maximum capacity of its battery.

$$\Upsilon_{\mathcal{USG}}(\theta) \geq Z(\theta); \quad \forall \theta \in [0^\circ, 360^\circ) \quad (23)$$

$$\Upsilon_{\mathcal{USG}}(\theta) = \max \Gamma(\theta) \quad (24)$$

$$\Gamma(\theta) = \left\{vw | vw \in R_+^0 \wedge \forall_{k \in \{1K\}} bat^k(\theta, vw) \leq CAP\right\} \quad (25)$$

$$bat^k(\theta, vw) = \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{n} x_{i,j}^k \times t_{i,j} \times P_{i,j}^k(\theta, vw) \quad (26)$$

$$P_{i,j}^k(\theta, vw) = \frac{1}{2} C_D \times A \times D \times \left(va_{i,j}(\theta, vw)\right)^3 + \frac{\left((ep + f_{i,j}^k) \times \mathrm{g}\right)^2}{D \times b^2 \times va_{i,j}(\theta, vw)} \quad (27)$$

Variables $va_{i,j}(\theta, vw)$ and $t_{i,j}$ depend on the assumed strategy for deliveries. If the ground speed $vg_{i,j}$ is constant, then the air speed $va_{i,j}$ is calculated as follows:

$$va_{i,j}(\theta, vw) = \sqrt{\left(vg_{i,j} \times cos\vartheta_{i,j} - vw \times cos\theta\right)^2 + \left(vg_{i,j} \times sin\vartheta_{i,j} - vw \times sin\theta\right)^2} \quad (28)$$

$$t_{i,j} = \frac{d_{i,j}}{vg_{i,j}}. \quad (29)$$

Where the course angle $\vartheta_{i,j}$ and the travel distance $d_{i,j}$ are known and they are calculated based on the nodes' geographic coordinates $pn_i = (\phi_i, \lambda_i)$ [46, 47] (R means the radius of the Earth $R = 6371.009[km]$):

$$d_{i,j} = R \times \sqrt{\left(\phi_j - \phi_i\right)^2 + \left(\cos\left(\frac{\phi_i + \phi_j}{2}\right) \times (\lambda_j - \lambda_i)\right)^2} \quad (30)$$

$$\vartheta_{i,j} = arctg\left(\frac{\lambda_j - \lambda_i}{\phi_i - \phi_j}\right) \quad (31)$$

Customer's satisfaction. The previous study [39] has indicated that it might be difficult to define equitable aid distribution among recipients. For modelling purposes we assume that the equitable aid distribution is measured by the Customer's Satisfaction Level (CSL). Customer's satisfaction is expressed, as a % of the expected amount of goods that are delivered to the recipients:

$$\frac{\sum_{i=1}^{n} cp_i}{\sum_{i=1}^{n} z_i} \times 100\% \geq CSL. \quad (32)$$

In the example from Fig. 2 customer's satisfaction equals $CSL = 100\%$ (the mission plan assumes delivery of the entire amount of the expected goods z_i). The CSL should be equal or higher than the value arbitrarily assumed by a decision maker. In the proposed approach it is possible to consider the plans of missions where not all goods are delivered, thus ensuring a certain level of CSL lower than 100 %.

Constraints (2)-(11) describe the relationship between routes (represented by the variables $x_{i,j}^k$) and the delivery schedule (variables y_i^k and s^k). They provide, among others, that it is not possible to take off several UAVs from the base at the same time (4), a recipient cannot by simultaneously served by several UAVs (6), deliveries are made in accordance with the adopted route (7), (8), it guarantees closed loops of the routes (9). Constraints (12)-(22), link UAV routes ($x_{i,j}^k$) to the amounts of delivered goods (variables c_i^k). They also ensure that the UAVs are not overloaded (14), correct amounts are delivered (17). Constraints (19)-(22) determine the weight ($f_{i,j}^k$) of the goods at each section of the taken route. Constraints (23)-(31) describe the values of the determined resistance functions $\Upsilon_{\mathcal{USG}}(\theta)$ for the fleet U and ensure that these values exceed the value of the function $Z(\theta)$ (for forecasted weather conditions). The value of the $\Upsilon_{\mathcal{USG}}(\theta)$ resistance functions depend on the amount of energy consumed by a UAV in flight which in turn depends non-linearly on the speed value $va_{i,j}$ - see Fig. 6. It means that some of the constraints, e.g. (26)-(27), in the adopted model have a non-linear character, thus implying the necessity to use the capabilities of declarative environments (in particular constraints programming).

5 Problem formulation

The introduced model allows defining a robust plan of UAV missions. We consider a fleet $\mathcal{U}$ that delivers to the customers allocated in a network G. The problem is defined as follows:

Does a plan of mission S (determined by variables Π, Y, C) exist, that ensures robustness to the given weather $\Upsilon_{\mathcal{USG}}(\theta) \geq Z(\theta)$ (constraints (23)-(31)) while maintaining the required customer's satisfaction level CSL (32)?

The investigated problem can be seen as a Constraint Satisfaction Problem (CSP) described, as (33):

$$CP = (\mathcal{V}, \mathcal{D}, \mathcal{C}), \quad (33)$$

Where:

$\mathcal{V} = \{\Pi, \mathcal{Y}, \mathcal{C}\}$ - a set of decision variables which are determining a plan of 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,

$\mathcal{C}$ - a set of constraints specifying the relationships between UAV routes, UAV schedules, and transported materials formulas (2)–(32).

To solve the CP defined in formula (33), the values of the decision variables need to be found for which all the constraints are satisfied. By implementing CP in a constraint programming environment, such as IBM ILOG, an answer to the above formulated question is searched.

6 Model Application - Computational Experiments

The proposed model has got a practical application. It is designed to facilitate the decision making (DM) on UAV's mission planning in changing weather conditions. It enables defining multiple scenarios for changing weather forecasts, by:

- [DM1] Assessing the existing plans in terms of their feasibility under the given conditions (as defined by function $Z(\theta)$)
- [DM2] Finding plans, that are robust ($\Upsilon_{\mathcal{USG}}(\theta)$) to the given weather conditions
- [DM3] Identifying areas, which are not accessible in the given weather conditions.
- [DM4] Planning of emergency returns of UAVs, or complementary missions, when the real weather conditions are more difficult than those indicated by the available forecast.

In order to present the application of the model for DM1-DM4 we use the case presented in Fig. 2b. In the initial case the mission cannot be completed for the conditions: $vw = 10\ \frac{m}{s}$; $\theta = 150°$ as, the battery would discharge in U_1. First the developed model is used to determine DM2:

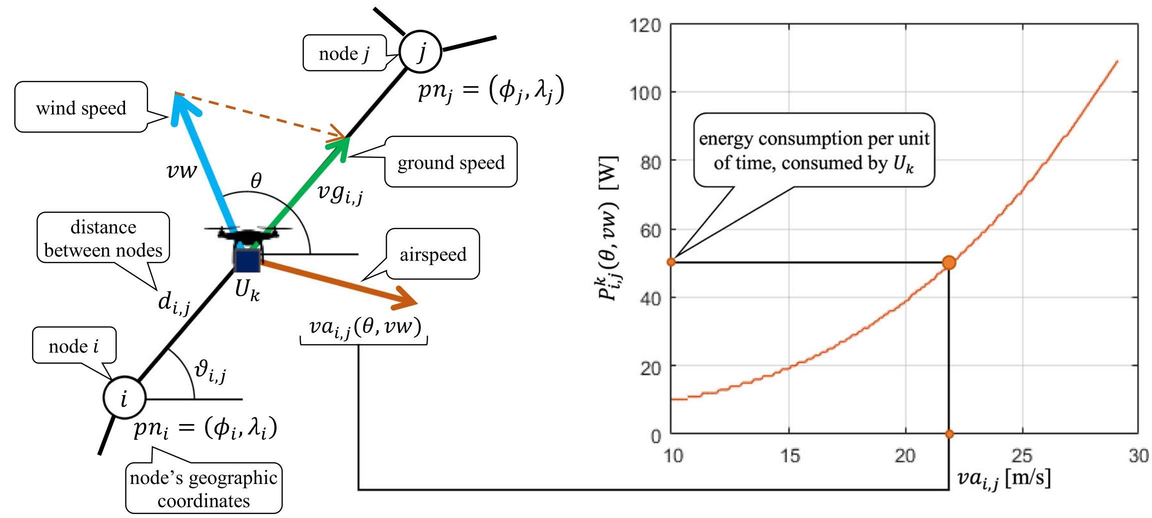

Fig. 6 Graphic illustration of the nonlinear dependence of the $P_{i,j}^k(\theta, vw)$ on the $va_{i,j}(\theta, vw)$

> A proactive plan of mission S for fleet $\mathcal{U}$ ensuring timely delivery of all expected essential goods($CSL = 100\%$) if weather conditions change to: $vw \in \left[0\frac{m}{s}, 10\frac{m}{s}\right]; \theta \in [0°, 360°)$.

Thus, the decision maker search for a plan of mission that enables the delivery of essential goods to all collection points when the wind speed does not exceed $10\frac{m}{s}$ regardless of the wind direction (DM2). Figure 7a presents the graph of function $Z(\theta)$ and the solution of the problem using Eq. (33). The declarative programming environment IBM ILOG (Intel Core i7-M4800MQ 2.7 GHz, 32 GB RAM) is used. The solution obtained after 1 s was negative, i.e. no mission S was found. Figure 7b presents the graph of function $\Upsilon_{\mathcal{USG}}(\theta)$, which corresponds to the best (i.e. maximizing the value of $\sum_{\theta=0}^{360}(\Upsilon_{\mathcal{USG}}(\theta) - Z(\theta))$) of obtained solutions. The value of function $\Upsilon_{\mathcal{USG}}(156) = 9.3\frac{m}{s}$ is smaller than the expected value of $10\frac{m}{s}$. It means that, for the forecasted weather conditions (e.g. those marked in gray in Fig. 7b) the planned mission would not be completed, as not all of the planned deliveries would be made.

An alternative scenario with additional UAV$_4$ is tested to find a proactive plan for the fleet $\mathcal{U} = \{U_1, U_2, U_3, U_4\}$. When the problem is solved again for the fleet $\mathcal{U} = \{U_1, U_2, U_3, U_4\}$, the first acceptable solution is obtained in 559 s. Tasks performed by UAVs U_2, U_3 are carried out in the same way as shown in Fig. 2, while tasks initially performed by U_1 are partly taken over by U_4.

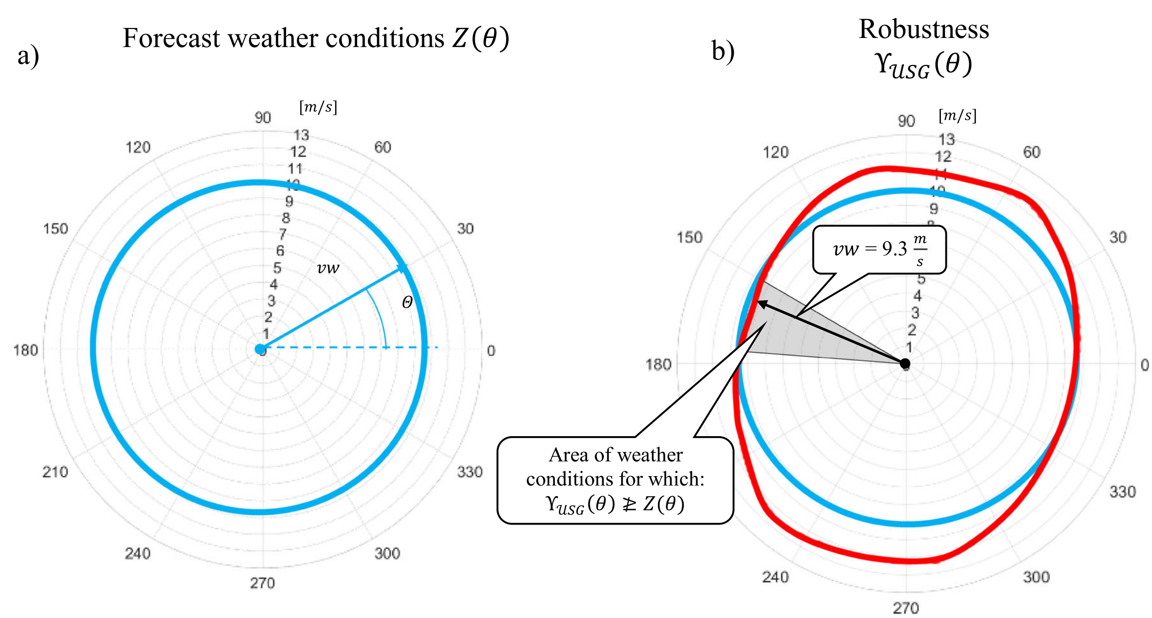

Fig. 7 Function $vw(\theta)$ determining the upper value of wind speed for changing wind direction for fleet $\mathcal{U} = \{U_1, U_2, U_3\}$

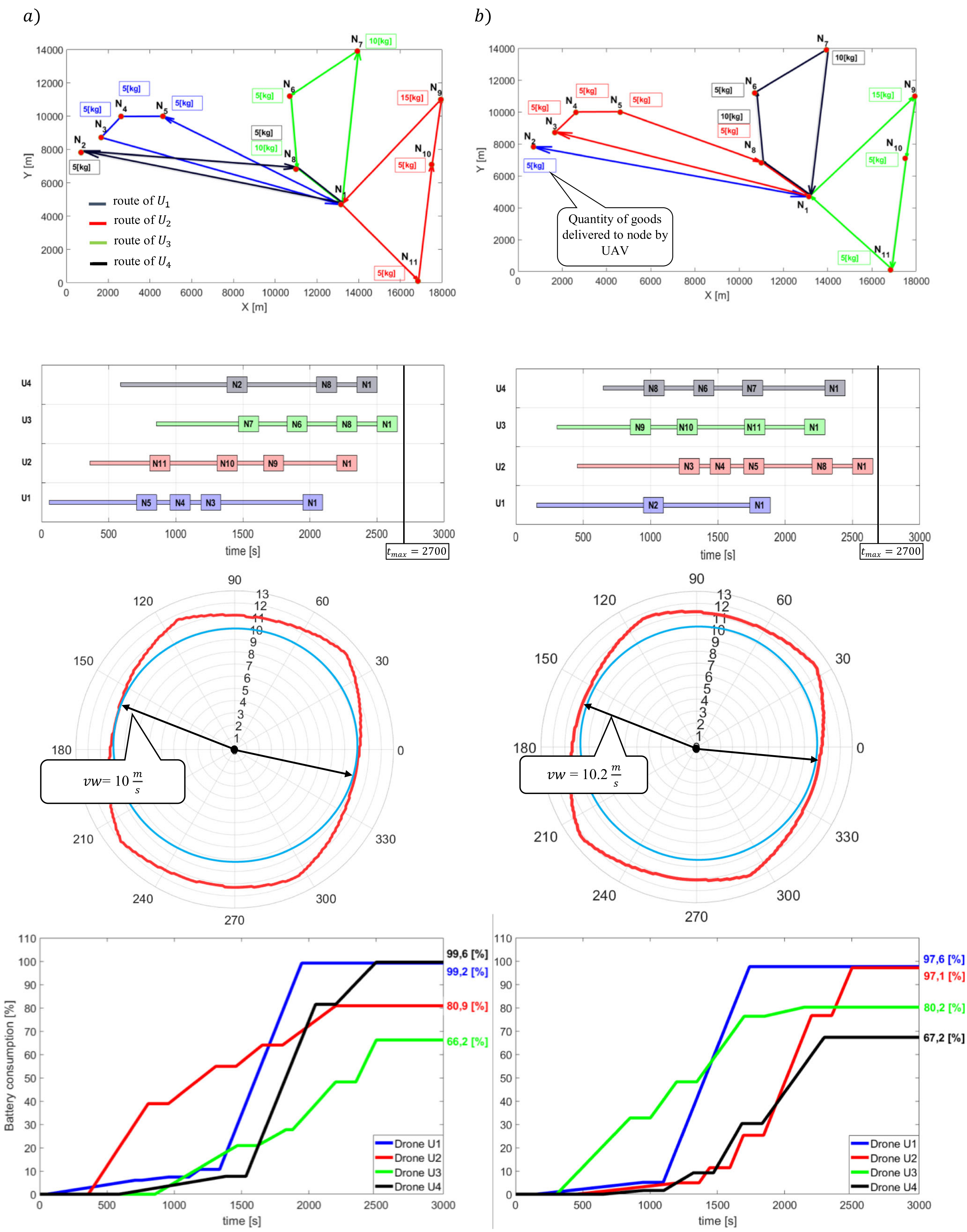

Fig. 8 Solutions received for fleet $\mathcal{U} = \{U_1, U_2, U_3, U_4\}$

Figure 8 presents the obtained solution, which consists of the routes for the new fleet $\mathcal{U} = \{U_1, U_2, U_3, U_4\}$: $\pi_1 = (N_1, N_5, N_4, N_3, N_1)$, $\pi_2 = (N_1, N_{11}, N_{10}, N_9, N_1)$, $\pi_3 = (N_1, N_7, N_6, N_8, N_1)$, $\pi_4 = (N_1, N_2, N_8, N_1)$. The corresponding supply schedule Y, robustness chart $\mathrm{Y}_{\mathcal{USG}}(\theta)$ and battery consumption chart corresponding to the worst weather conditions ($\theta = 156^\circ, vw = 10\frac{m}{s}$) are included. The battery consumption for $= 156°$ is respectively: 99.2%, 80.9%, 66.2 and 99.6% and when $\theta = 345°$ is respectively: 99.7%, 81.6 %, 68.7 and 99.9%. An alternative solution is presented on Fig. 8b, in which the routes of all UAVs have changed. When the fleet $\mathcal{U}$ is replenished by an additional UAV then it allows for the obtaining of a plan of mission S that ensures timely delivery of expected goods in the forecasted weather conditions $Z(\theta)$.

In practice, it often happens that the actual conditions differ from the forecasts. In such situations a decision maker needs to plan the emergency return of UAVs to the base (DM3-DM4). In Fig. 9 are shown the return paths for each UAV, which corresponds to the scenario from Fig. 8a. The decision to return of U_k to the base is taken when a battery level $TH^k_{v_i}$ (i.e., the battery level in real weather conditions) at v_i is lower than $BTH^k_{v_i}$ (i.e. the minimum battery level for the forecasted weather conditions):

$$BTH^k_{v_i} = BC^k(v_i, v_{i+1}) + BC^k(v_{i+1}, v_1), v_i, v_{i+1} \in N \qquad (34)$$

where $BC^k(v_a, v_b)$ is the energy needed to pass between nodes $v_a, v_b \in N$ (for forecasted weather conditions):

$$BC^k(v_a, v_b) = t_{a,b} \times \max_{\substack{\theta \in [0,360) \\ vw \in [0, vw']}} \left\{ P^k_{a,b}(\theta, vw) \right\} \qquad (35)$$

where $P^k_{a,b}(\theta, vw)$ is calculated from (27) and vw' denotes maximum forecasted wind speed. The value of the threshold $BTH^k_{v_i}$ is a sum of the energy required when passing to the next point $BC(v_i, v_{i+1})$ and possible return to base $BC(v_{i+1}, v_1)$.

Thus, in the proposed approach it is assumed that the decision to return U_k to base is made when the following condition is met:

$$TH^k_{v_i} < BTH^k_{v_i} \qquad (36)$$

To illustrate the decision type DM3 (Identifying areas not accessible in the given weather conditions) and type DM4 (planning of emergency returns of UAVs), we analyze a scenario, when the deteriorating weather conditions exceed the forecasted value $Z(\theta)$ e.g., $\theta = 156^\circ, vw = 12\frac{m}{s}$. In this situation, not all of UAVs are able to perform their tasks. The UAV U_1 is able to deliver articles only to recipient N_5, as at point N_5 the battery's level of the U_1 (94.6%), is too low to continue the mission. The UAV U_4 also would not be able to fulfill its mission, as the energy needed during the delivery along the route $\pi_4 = \{N_1, N_2, N_1\}$ exceeds its limit by 18.7 % (see Fig. 10). The inability to deliver goods to some recipients means that customer's satisfaction is lower than 100%: CSL = 73.3% (as 55kg are delivered, when 75kg are planned). The planned amount of goods would be delivered only to points $N_5, N_6, N_7, N_9, N_{10}, N_{11}$. In other cases, the volume of planned deliveries would be only partially satisfied, as e.g., at point N_8 (66.6% of needed goods are delivered) and none of deliveries are made at collection points N_2, N_3 and N_4. Thus, it is necessary to make another attempt to deliver, e.g., by using an inactive UAV U_4. However, it turns out that any subsequent additional delivery is only possible for collection point N_8. The collection points N_2, N_3 and N_4 remain out of range of the fleet $\mathcal{U}$ (direct flight to these points requires energy exceeding the available battery level). It means that the deliveries to these points are only possible when the weather conditions would change, and wind speed is $vw \leq 10\frac{m}{s}$.

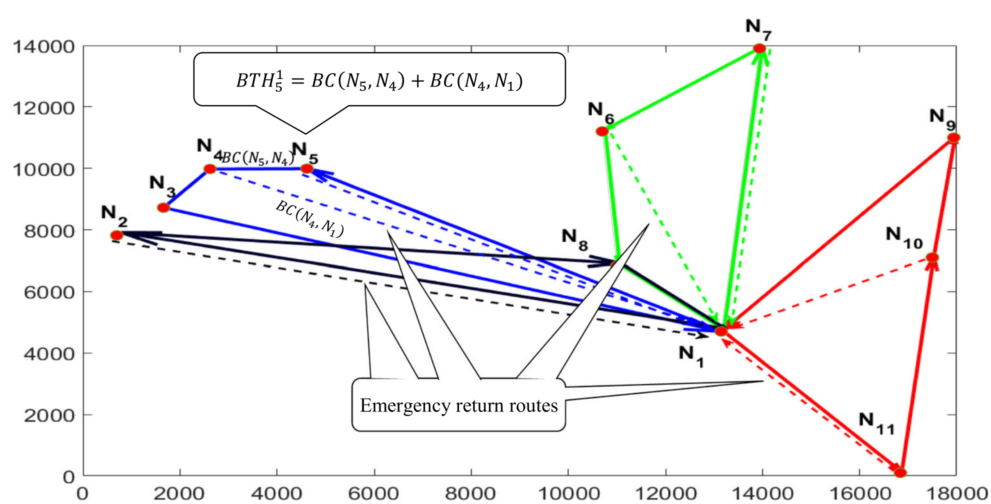

Fig. 9 Return routes in case of worsening of the weather conditions

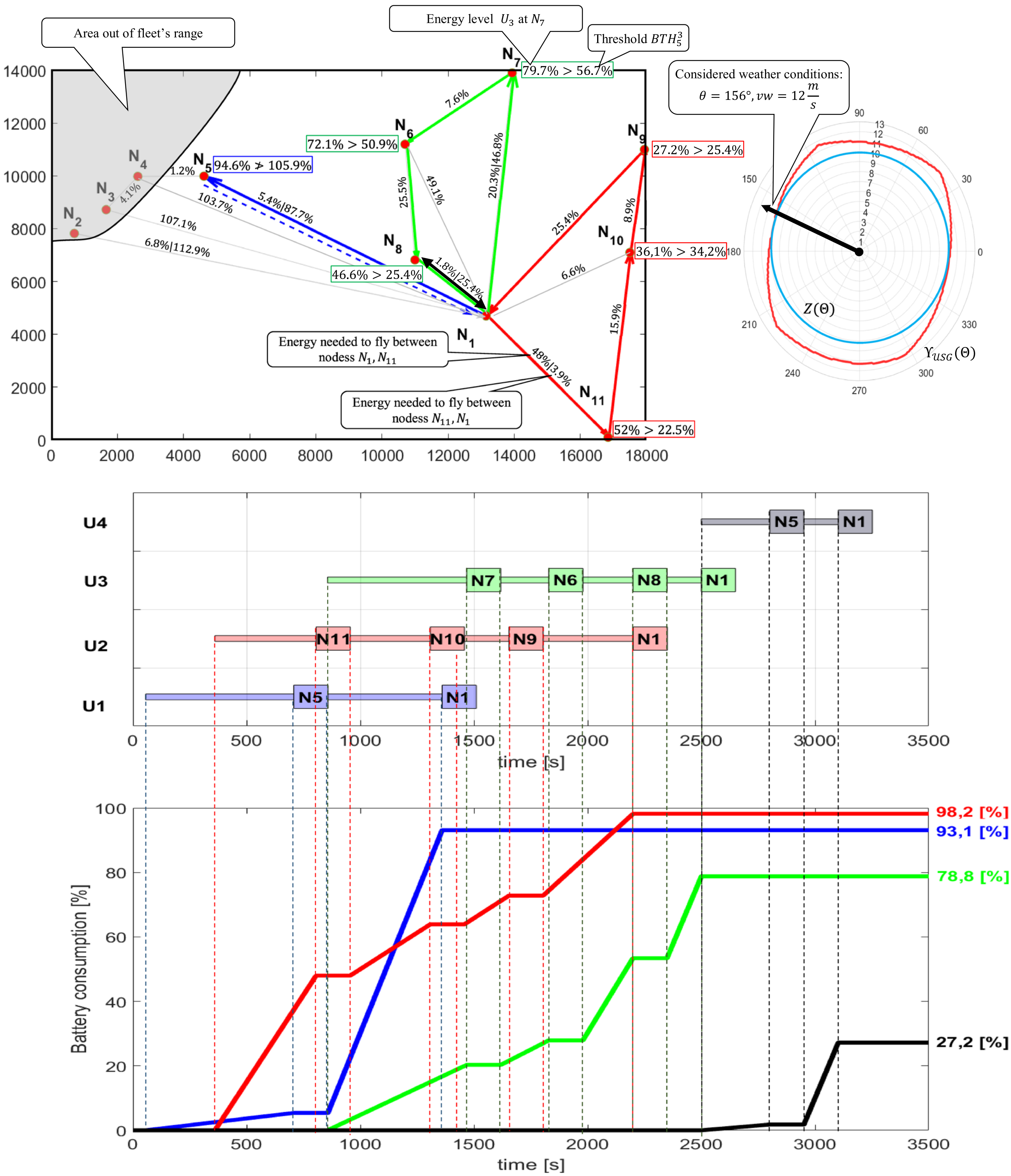

Fig. 10 Deliveries in the weather conditions: $\theta = 156°, vw = 12\frac{m}{s}$

In our model we link decision making on the "route discovery" (proactive route planning), and "route maintenance" (reactive rules adopting). Thus, the model enables creating plans of mission, which are robust to sudden changes in weather conditions. Consequently the need to react in such task-dependent situations enforces the establishment of condition-action rules that allow for the designation of appropriate possible end-to-end routes, and enabling emergency

Table 3 Results of the selected experiments

n	K	$Z(\theta) = 9\frac{m}{s}\ \forall\theta \in [0^\circ, 360^\circ)$ TC [s]	$Z(\theta) = 10\frac{m}{s}\ \forall\theta \in [0^\circ, 360^\circ)$ TC [s]	$Z(\theta) = 11\frac{m}{s}\ \forall\theta \in [0^\circ, 360^\circ)$ TC [s]	NC	NDV
4	2	5.11	4.06	4.04	454	1110
	3	4.48	4.52	4.39	825	2341
	4	4.9	4.77	4.9	1296	4024
5	2	4.12	3.77	3.86	705	1921
	3	4.57	4.25	4.23	1308	3757
	4	5.75	5.19	4.05	2083	7245
6	2	4.71	4.72	5.6	1084	3360
	3	6.88	6.52	6.78	2115	7707
	4	16.34	47.51	13.7	3478	13,834
7	2	5.05	5.07	4.73	1671	5907
	3	11.1	11.39	8.9	3486	14,431
	4	21.45	13.21	13.92	5961	26,671
8	2	10,29	11,1	12.48	2546	10,042
	3	119.7	34.98	16.95	5561	25,769
	4	52.46	70.09	72.13	10,012	48,636
9	2	60.49	9.91	7.12	3613	15,189
	3	200.38	262.28	87.12	8352	39,993
	4	314.53	321.75	345.65	15,055	76,273
10	2	93.07	52.33	20.99	4920	21,636
	3	253.8	326.65	340.08	11,703	57,967
	4	446.43	458.75	480.04	21,378	111,310
11	2	96.25	84.65	89.25	6531	26,767
	3	258.36	298.55	254.97	15,906	80,843
	4	501.21	520.45	595.7	29,365	156,051
12	2	268.56	272.18	289.47	8448	32,898
	3	t>600	t>600	t>600	21,006	108,720
	4	t>600	t>600	t>600	38,852	210,892

n – number of nodes; K – size of the UAV fleet; TC – time of computation (s); NC – number of constraints; NDV – number of decision variables

safe completion of the mission or its continuation in a modified version.

The applicability of the model for online decision-making (solving time < 600 s) is tested by a series of quantitative experiments. Table 3 contains the results of experiments that are conducted for the three functions of forecasted weather $Z(\theta)$. The experiments are carried out for a network of n randomly designated collection points and a fleet consisting of K UAVs with the technical parameters, as shown in Table 2. The numerical examples present an application of the developed model for crisis management in residential areas affected by floods. For that reason it is assumed $CSL = 100\%$, as all residents in need should receive the designated delivery.

UAVs move with a constant ground speed $vg = 20\frac{m}{s}$ (strategy in which the air speed va is adapted to the weather conditions to maintain a constant value of vg). The conducted experiments show that the robust plan of missions can be found for a network of 11 (or less) collection points.

7 Conclusions

The proposed declarative model (implemented in the ILOG IBM environment) allows to determine the scenarios for disaster relief mission that are robust to the changes in weather conditions. Since the related problem of planning of a UAV mission has proven to be NP-hard. The computational complexity of such problem, sets up a base for the requirement on application of approximation or heuristics approaches, as opposed to usage of exact but intractable algorithms for solving them [48]. The constraint satisfaction driven approach has been proposed, in order to tackle the time-consuming calculations for most of the practical cases. The presented experiments allow for quantitatively assessing the scale of distribution network for which the developed approach guarantees obtaining a reactive response in online mode, i.e., in time $t < 600$ s. These experiments take into account the actual flight characteristics of the UAVs and forecasted weather conditions in order to ensure a sufficient level of realism for comparisons. Proactive scenarios take into consideration the influence of weather conditions on energy consumption and allow for identifying a plan of mission, which is robust to the specific changes in weather conditions. In addition to the proactive scenarios, also the reactive scenarios are prototyped. The reactive scenarios link the fleet's size with assumed size of deliveries and changes in the weather forecast during missions. To our best knowledge, it is the first model for the solving a problem with the above-mentioned properties. The presented problem is neither previously addressed nor solved in existing literature, thus it is not possible to compare it directly with existing methods.

The main advantage of our model is its open structure, that allows taking into account several other variables and restrictions (e.g., related to the cost of a mission, infrastructure of a distribution system, heterogeneity of UAVs, etc.). In addition, the model allows for assessing the possibilities of carrying out a planned mission with assumed infrastructure constraints, as well as designing infrastructure, which ensures the implementation of a planned mission.

The main limitation of the proposed approach is relatively long computing time, as a result its use in online mode is suitable only for cases with few delivery points. However, as the previous study has shown, the typical conditions for planning and routing of disaster relief mission include a small number of destinations per trip [9].

In our future research, we want to take into account the uncertain nature of the real world variables which are not deterministic. Thus, a fuzzy approach will be applied for problem solving. The scope of the current paper is limited to the modelling of robust delivery scenarios for the selected disturbances. We consider the re-planning when disturbances appear (e.g., earlier return some of the UAVs from the fleet to the base), which exceeds the values incorporated at the proactive planning stage. The related topic of the robustness in the control of UAV (especially in the presence of wind gusts) is an interesting direction for our future research. Finally, the model may benefit from adding different aspects related to fleet sizes with heterogeneous UAVs, as well as the coordination of different UAV fleets operating independently in shared area.

Author Contributions All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Radzki Grzegorz, Golińska-Dawson Paulina, Bocewicz Grzegorz. The literature review and research gaps were provided by Radzki Grzegorz, Golińska-Dawson Paulina. Declarative model of considered problem was proposed by Radzki Grzegorz, Bocewicz Grzegorz, Banaszak Zbigniew. The first draft of the manuscript was written by Bocewicz Grzegorz, Banaszak Zbigniew, and the revisions were done by Radzki Grzegorz, Golińska-Dawson Paulina. All authors read and approved the final manuscript.

Data Availability The data that supports the findings of this study is available from Bocewicz Grzegorz and Radzki Grzegorz under request.

Code Availability Not applicable

Declarations

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Conflict of Interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

Consent to Publish Not applicable.

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