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Optimal Multi-UAV Path Planning for Monitoring in Windy Conditions and under Uncertainty

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Abstract

Nowadays, due to the advances in Unmanned Aerial Vehicles (UAV) technology, they are used in various applications, including surveillance and imaging of various areas. In this paper, the problem of routing UAVs to image specific areas with different accuracy requirements is investigated. The mission planning was done considering different weather conditions and wind currents, and the uncertainty in wind speed, which affects the final speed of the drone, was investigated. A mathematical model was presented to determine the optimal flight paths of the drones, while taking into account the imaging accuracy that is adjusted by altitude. Computational experiments were performed to investigate the problem and the presented model using the GAMS software.

Keywords: Unmanned aerial vehicle, Mission planning, Drone, Aerial monitoring, Vehicle routing problem, Mathematical model.

1 | Introduction

Emerging technologies are rapidly changing the way many industrial and scientific processes are conducted. One of these technologies is drones, or UAVs, which have become especially important in the field of aerial imaging. The use of drones in aerial imaging is growing quickly due to the unique characteristics of these devices, including easy accessibility, low cost, ability to observe large areas, high precision, and the ability to fly in challenging locations [1]. In recent years, UAVs have been used in a variety of applications such as aerial photography and mapping, environmental monitoring, agriculture and forestry, crisis search and rescue, cargo transportation, environmental research, and photography and videography. By installing special imaging sensors, drones can capture desired aerial images, and the monitored images can be transmitted to control

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stations via a wireless transmission system [1–3]. Drones are being developed to be able to plan their own routes to move from one location to another and avoid obstacles in their path. However, if the drone is not operating autonomously, mission planning is very important for routing and the desired activities. A mission plan involves an optimization problem that satisfies the mission objectives and constraints [4]. Mission planning for drones is planning the route between target locations and the necessary actions (loading/unloading cargo, taking video or photos, gathering information) within a given time frame [5].

The factors influencing the flight of imaging drones can be categorized into three main groups: environmental, technical, and human-related. Weather conditions such as wind, temperature, and precipitation significantly affect flight stability and image quality. In addition, magnetic interference and physical obstacles can disrupt navigation systems. On the technical side, battery capacity, motor type, GPS accuracy, and the quality of the camera are critical to drone performance. Furthermore, the operator's expertise and proper flight planning are essential human factors that contribute to the success of aerial imaging missions [6]. In this paper, wind is considered as an environmental factor, taking into account the uncertainty of its speed prediction and its effect on the final direction and speed of the UAV flight.

The Vehicle Routing Problem (VRP) was first studied by Dantzig and Ramser [7]. After their work, this topic has been widely studied in research. With the increasing use of UAVs in human life, attention to this device has increased in recent years. Various studies have studied the technical aspects of UAVs, such as control, endurance, structural shape, and other characteristics (see [8] and [9]). Also, several researchers have studied the planning and use of UAVs in VRP. The authors in [10] investigated a multi-objective VRP with time window and UAV transportation constraints. In Study [11], the authors investigated the routing problem of cargo drones, taking into account weather conditions and their impact on drones' flight. The authors in [12] presented a multi-objective model with the aim of reducing costs, delivery delays, pollution, and accident risk while considering the risk of epidemic diseases. In their study, the possibility of transporting food packages by air (with drones) and land was provided, and the goal was to optimize vehicle routing. Also, numerous papers have examined the problem of routing imaging drones. The authors in [1] investigated the problem of monitoring different areas with imaging sensitivity, so that the goal of the presented model is to reduce the total imaging time. The authors in [13] investigated optimal UAV routing in search and rescue missions, which include search, inform, and monitor. The authors in [14] proposed a neural network model for detecting and locating objects, such as buildings, as well as an optimization method for finding the optimal flight path for accurate object detection with minimal time cost. The authors in [15] investigated and studied the flight path of drones to monitor the progress of construction sites. The authors in [16] examined the use of drones equipped with thermal imaging cameras to identify and track wildlife in different areas. They mainly focused on designing the flight path of the UAVs to provide the best results in animal identification in natural environments.

This paper is organized as follows. In Section 2, the problem statement is explained, the mathematical model is formulated, and the non-fuzzy model is presented. Numerical experiments are reported in Section 3, and Section 4 analyzes the results. Finally, Section 5 concludes the paper and outlines further research directions.

2 | Problem Statement

2.1 | Problem Description

In this section, a planning model is proposed for the UAV monitoring problem. This model determines the flight paths of the UAV as well as the surveillance height, taking into account the weather conditions. Each surveillance area has a specific surveillance requirement level that must be met by drones. Since wind speed and direction affect the speed of UAVs and their monitoring time, the objective of the model is to minimize the total time required to complete all monitoring tasks. The mission planning problem is investigated to identify flight paths to monitor the covered areas on a specific network including nodes and flight altitudes. The movement of the UAV between the nodes will be in the form of perpendicular movements so that first the UAV moves horizontally and then the monitoring height is adjusted with the vertical movement of the

UAV. Therefore, the distance between two nodes (i,r) and (j,s) is defined as Manhattan distance. The monitoring height of the UAV changes according to the required monitoring accuracy, so that a lower height covers more accuracy and a smaller area, and a higher height covers less accuracy and a wider area. *Figures 1* and *2* shows the flight height and how to cover the monitoring areas.

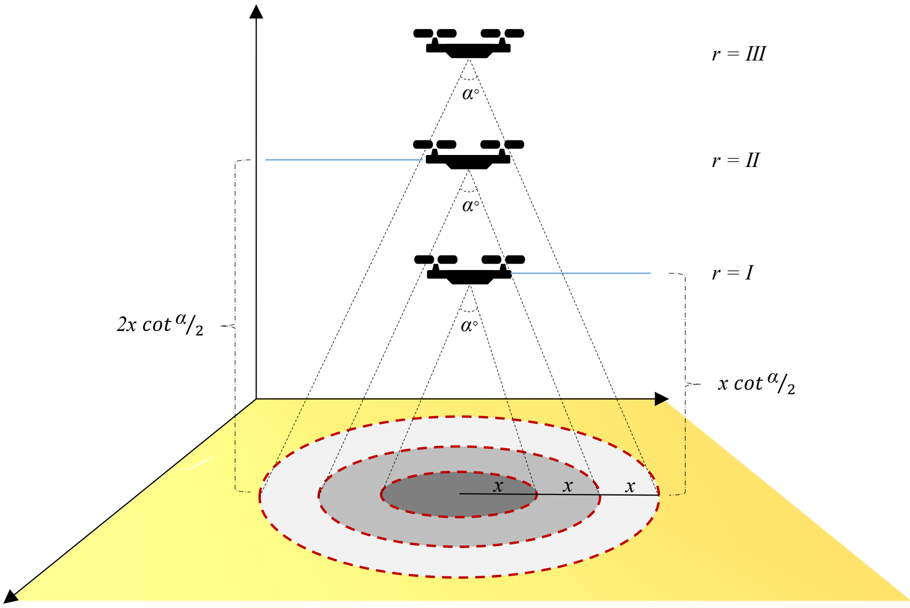

Fig. 1. Conceptual framework.

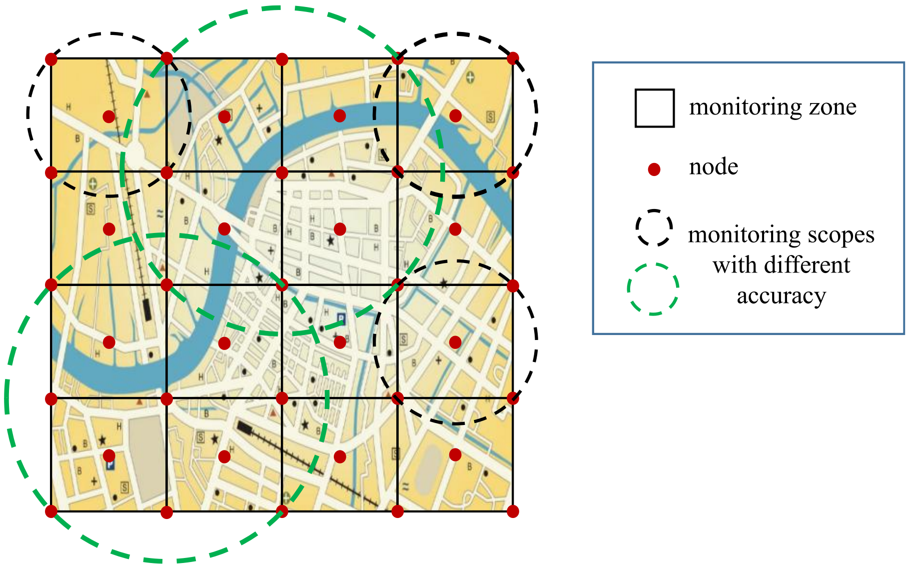

Fig. 2. An example of how drones monitor [1].

The final speed of the UAV changes under the influence of the wind speed and direction, so that if the x-y coordinate axis is assumed to be a horizontal surface and the z-w coordinate axis is assumed to be a vertical surface (where w is in the direction of the wind), the final speed of the UAV is according to *Eq. 1* for horizontal plane and according to *Eq. 2* for vertical plane. According to *Figure 3*, the final speed of the UAV according to a fixed nominal speed, as well as hypothetical nodes, is provided for the example. The notations used in equations are explained in Section 2.2.

$$\mathrm{vf_{ijk}} = \sqrt{\left(\mathrm{vn_k} \times \cos\varphi_{ij} + \widetilde{\mathrm{vw}} \times \cos\delta\right)^2 + \left(\mathrm{vn_k} \times \sin\varphi_{ij} + \widetilde{\mathrm{vw}} \times \sin\delta\right)^2}, \tag{1}$$

$$\mathrm{vf_{rsk}} = \sqrt{(\mathrm{vn_k})^2 - (\widetilde{\mathrm{vw}})^2}, \tag{2}$$

$$\varphi_{ij} = \omega_{ij} - \arcsin\left[\frac{\widetilde{\mathrm{vw}}}{\mathrm{vn_k}}\sin(\delta - \omega_{ij})\right]. \tag{3}$$

Finally, according to the above relationships, the travel time between different nodes at different heights is calculated as follows.

$$\mathrm{t_{irjsk}} = \left(\frac{\mathrm{d_{ij}}}{\mathrm{vf_{ijk}}}\right) + \left(\frac{\mathrm{dd_{rs}}}{\mathrm{vf_{rsk}}}\right). \tag{4}$$

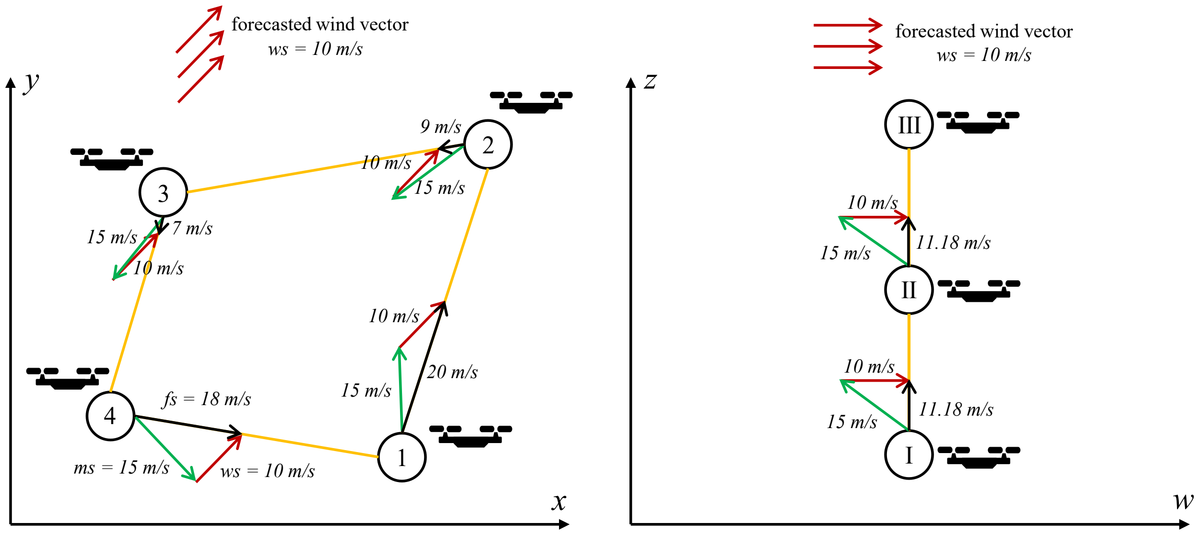

Fig. 3. An example of the final speed of the drone moving between different nodes horizontally [11] and different heights vertically.

2.2 | Notations and Definitions

In this section, the notations to be used in this study are introduced as follows.

Sets	
I & J	The set of nodes.
R & S	The set of flight heights.
A	The set of monitoring areas.
K	The set of UAVs.
Parameters	
t_{irjsk}	Time required by UAV k to move from node (i,r) to (j,s).
m_{ir}	Time required by a UAV staying at node (i,r) to monitor.

c_{air}	1 if monitoring area a can be covered by a UAV that stops at node (i,r) and the monitoring accuracy requirement is also satisfied, and 0 otherwise.
TM_k	maximum flight time of UAV k.
d_{ij}	The distance between node i and node j at the same flight height.
dd_{rs}	The distance between flight height r and flight height s.
ω_{ij}	Angle of the motion vector relative to the coordinate plane when the UAV moves from node i to node j at the same flight height.
δ	Wind direction vector relative to the coordinate plane.
$\widetilde{vw}$	Wind speed; it is considered a triangular fuzzy number, TFN (vw1,vw2,vw3).
vn_k	The nominal speed of the UAV k.
vf_{ijk}	Final speed of the UAV k (influenced by wind speed and direction), travelling from node i to node j.
vf_{rsk}	Final speed of the UAV k (influenced by wind speed and direction), travelling from flight height r to s.
φ_{ij}	Angle of the nominal speed vector when the UAV travels from node i to node j.
Decision variables	
X_{irjsk}	1 if UAV k moves from (i,r) to (j,s) and 0 otherwise.
Y_{irk}	1 if UAV k stops at node (i,r) to monitor and 0 otherwise.
U_{irk}	Number of nodes that have been visited by UAV k; it should be noted that $U_{00k} = 0$, and U_{irk} is not defined if node (i,r) is not visited by UAV k.

2.3 | Notations and Definitions

The main assumptions are as follows:

I. Each UAV tour must start and end at the same depot.

II. The distance between (i,r) and (j,s) is calculated as a Manhattan distance so that the drone first adjusts its height and then moves horizontally or vice versa.

III. Weather forecasting has already been done with sufficient accuracy and a certain tolerance.

2.4 | Model Formulation

$$Z_1 = \text{Min} \sum_i \sum_r \sum_j \sum_s \sum_k t_{irjsk} X_{irjsk} + \sum_i \sum_r \sum_k m_{ir} Y_{irk}, \quad (5)$$

s. t.

$$\sum_{i-\{0\}} \sum_{r-\{0\}} \sum_k c_{air} Y_{irk} \geq 1, \quad \forall a, \quad (6)$$

$$\sum_k Y_{irk} \leq 1, \quad \forall i-\{0\}, r-\{0\}, \quad (7)$$

$$\sum_j \sum_s X_{irjsk} = Y_{irk}, \quad \forall i, r, k, \quad (8)$$

$$\sum_j \sum_s X_{00jsk} = 1, \quad \forall k, \quad (9)$$

$$\sum_i \sum_r X_{ir00k} = 1, \quad \forall k, \quad (10)$$

$$\sum_{j}\sum_{s} X_{irjsk} = \sum_{j}\sum_{s} X_{jsirk}, \qquad \forall i, r, k, \tag{11}$$

$$\sum_{i}\sum_{r}\sum_{j}\sum_{s} t_{irjsk} X_{irjsk} + \sum_{i-\{0\}}\sum_{r-\{0\}} m_{ir} Y_{irk} \leq TM_k, \quad \forall k, \tag{12}$$

$$U_{00k} = 0, \qquad \forall k, \tag{13}$$

$$U_{j,s,k} \geq U_{irk} + 1 - |I| \times |R| \left(1 - X_{irjsk}\right), \qquad \forall i, r, j, s, k;\ (i, r) \neq (j, s), \tag{14}$$

$$U_{i,r,k} \leq |I| \times |R| - 1, \quad \forall i, r, k, \tag{15}$$

$$U_{i,r,k} \geq 0, \qquad \forall i, r, k, \tag{16}$$

$$X_{irjsk} \in \{0,1\}, \qquad \forall i, r, j, s, k, \tag{17}$$

$$Y_{irk} \in \{0,1\}, \qquad \forall i - \{0\}, r - \{0\}, k. \tag{18}$$

The objective *Function (5)* minimizes the total time required to perform the monitoring operation. *Constraint (6)* ensures that each area is covered by at least one drone while meeting the surveillance accuracy requirements. *Constraint (7)* ensures that there will not be more than one UAV stop at the same node. *Constraint (8)* expresses the relationship between the decision variables X_{irjsk} and Y_{irk}. *Constraints (9)* and *(10)* show that all tours of each drone start and end at node 0. *Constraint (11)* shows the conservation of current at different nodes. *Constraint (12)* specifies that the travel time and monitoring time of each drone cannot exceed its maximum allowed flight time. *Constraints (13)-(15)* are subtour elimination constraints. *Constraints (16)-(18)* define the types of variables.

2.5 | Credibility-Based Fuzzy Programming Model

The proposed model becomes non-fuzzy according to the mathematical programming methods and based on the credibility measure. To do this, we need both optimistic and pessimistic values as critical values. If ξ is a fuzzy variable and $\alpha \in (0,1]$, the optimistic and pessimistic values for the variable ξ at the α level are defined as follows (see [17-18]).

$$\xi_{sup}(\alpha) = \sup\{r | Cr(\xi \geq r) \geq \alpha\}, \tag{19}$$

$$\xi_{inf}(\alpha) = \inf\{r | Cr(\xi \leq r) \geq \alpha\}. \tag{20}$$

In this paper, the variable ξ is considered as a triangular fuzzy number, for example, $\xi = (a1, a2, a3)$. And it is assumed that $\alpha \geq 0.5$, so optimistic and pessimistic values are obtained as follows (see [20]).

$$\xi_{sup}(\alpha) = (2\alpha - 1)a_1 + (2 - 2\alpha)a_2, \tag{21}$$

$$\xi_{inf}(\alpha) = (2 - 2\alpha)a_2 + (2\alpha - 1)a_3. \tag{22}$$

Due to optimistic and pessimistic values, the problem constraints that include fuzzy parameters become non-fuzzy. If r is a definite value in the constraint, the following two equations are used to make the constraint non-fuzzy.

$$Cr(\xi \geq r) \geq \alpha \quad \Leftrightarrow \quad r \leq \xi_{sup}(\alpha), \tag{23}$$

$$Cr(\xi \leq r) \geq \alpha \quad \Leftrightarrow \quad r \geq \xi_{inf}(\alpha). \tag{24}$$

In the proposed model, wind speed is considered fuzzy; therefore, *Eqs. (1)*, *(2)*, and *(3)* are affected by the existing uncertainty and are transformed into non-fuzzy according to *Eqs. (19)* to *(24)*.

$$vf_{ijk} \leq \sqrt{\left(vn_k \times \cos\varphi_{ij} + [(2\alpha - 1)vw_1 + (2 - 2\alpha)vw_2] \times \cos\delta\right)^2 + \left(vn_k \times \sin\varphi_{ij} + [(2\alpha - 1)vw_1 + (2 - 2\alpha)vw_2] \times \sin\delta\right)^2}, \tag{25}$$

$$vf_{ijk} \geq \sqrt{\left(vn_k \times \cos\varphi_{ij} + [(2 - 2\alpha)vw_2 + (2\alpha - 1)vw_3] \times \cos\delta\right)^2 + \left(vn_k \times \sin\varphi_{ij} + [(2 - 2\alpha)vw_2 + (2\alpha - 1)vw_3] \times \sin\delta\right)^2}, \tag{26}$$

$$vf_{rsk} \leq \sqrt{(vn_k)^2 - [(2 - 2\alpha)vw_2 + (2\alpha - 1)vw_3]^2}, \tag{27}$$

$$\mathrm{vf}_{\mathrm{rsk}} \geq \sqrt{(\mathrm{vn}_k)^2 - [(2\alpha-1)\mathrm{vw}_1 + (2-2\alpha)\mathrm{vw}_2]^2}, \tag{28}$$

$$\varphi_{ij} \leq \omega_{ij} - \arcsin\left[\frac{[(2-2\alpha)\mathrm{vw}_2 + (2\alpha-1)\mathrm{vw}_3]}{\mathrm{vn}_k}\sin(\delta-\omega_{ij})\right], \tag{29}$$

$$\varphi_{ij} \geq \omega_{ij} - \arcsin\left[\frac{[(2\alpha-1)\mathrm{vw}_1 + (2-2\alpha)\mathrm{vw}_2]}{\mathrm{vn}_k}\sin(\delta-\omega_{ij})\right]. \tag{30}$$

3 | Numerical Experiment

3.1 | Experiment Details

To evaluate the presented model, a numerical example has been studied. For this purpose, a specific and divided area is considered, as shown in *Fig. 5*, which requires aerial monitoring operations. The indicated nodes indicate the points of monitoring by different drones. Accordingly, according to the degree of importance of imaging each area (according to *Table 1*), 3 drones at 3 different heights can perform monitoring. The flight speed of the drones is assumed to be the same (6 m⁄s), but the maximum flight duration is 600, 400, and 350 seconds, respectively. Also, wind speed is a fuzzy number (2m⁄s, 3m⁄s, 4m⁄s) and α=0.6.

The height that can be covered by each area indicates the sensitivity with which each area is imaged. Height 1 is the lowest possible height and has the highest accuracy, and height 3 is the highest drone imaging level, which has the lowest accuracy. For example, area 4 can be covered from all three heights, but area 1 will only be covered from height 1 due to the sensitivity required for imaging.

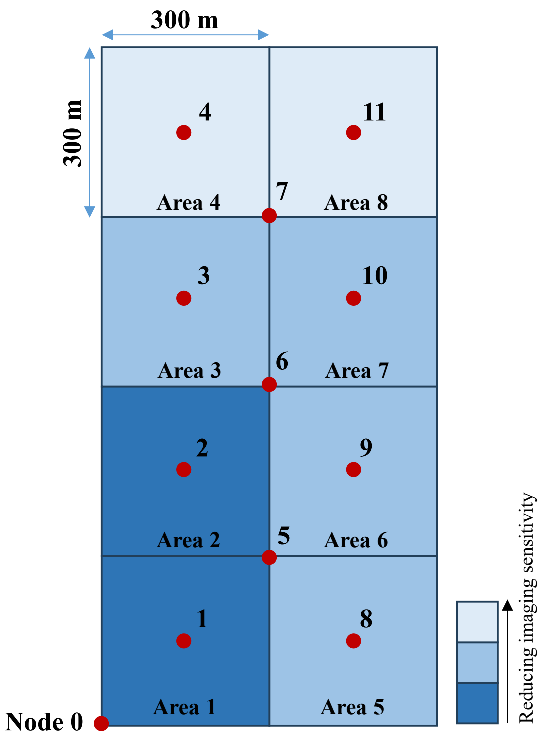

Fig. 4. The area to be monitored by a drone.

Table 1. Coverable height of each area

	Area							
	1	2	3	4	5	6	7	8
Coverable height	1	1	1-2	1-2-3	1-2	1-2	1-2	1-2-3

3.2 | Computational Results

By solving the mathematical model provided by the GAMS software, the results of the drones' routing for imaging the specified areas are obtained. *Fig. 5* shows the drones' stopping points and the imaging range of each drone. According to the results obtained, drone 1, moving from point 0 at the height of level 1, is stationed at point 1 and then goes to point 2 at the same level. Also, drone 3, moving from the starting point, first goes to the height of level 2 at point 5 and then goes to point 7 at the same level. The return of both drones will be to the initial origin. According to *Fig. 5*, areas 1 and 2 are monitored by UAV 1 with greater sensitivity, and areas 3 to 8 are imaged by UAV 3 with less sensitivity.

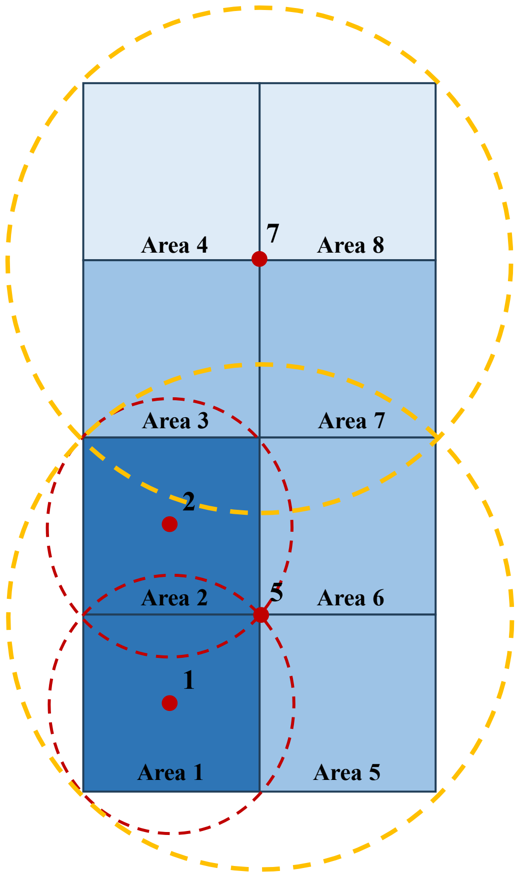

Fig. 5. Drones' stopping points and the imaging range.

4 | Evaluation

In the sensitivity analysis, changes in wind speed (with the same wind angle = 90^°) and wind direction (with the same wind speed = 3m/s) have been investigated. *Figs. 6* and *7* show the analyses performed.

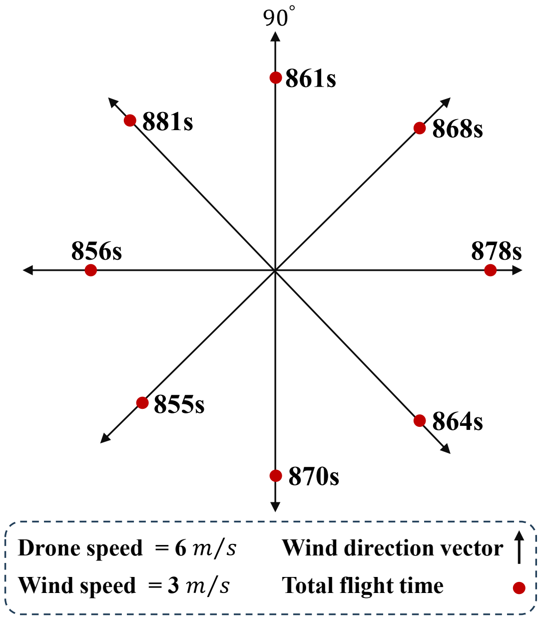

Fig. 6. Total flight time depending on wind angle changes.

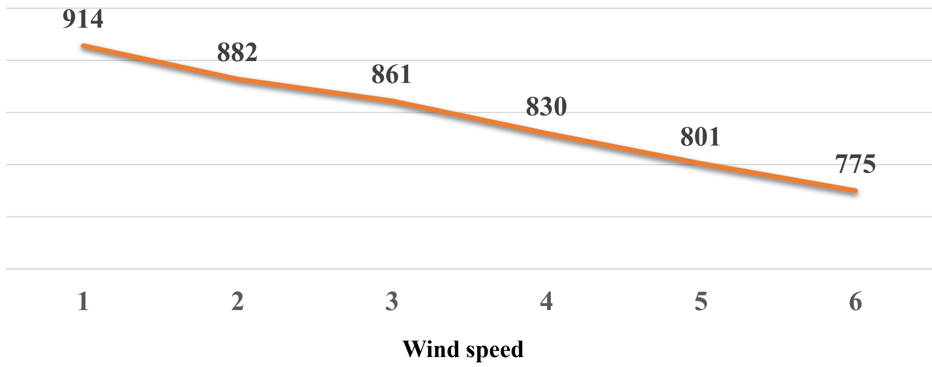

Fig. 7. Total flight time depending on wind speed changes.

5 | Conclusion

One of the important issues in transportation and logistics systems is the routing of land and air vehicles. The drone imaging routing problem refers to a problem in which the goal is to assign the desired areas for monitoring to each drone and determine the optimal movement paths. Nowadays, drones are used for a variety of purposes. Drones can be used for aerial mapping and surveillance of target areas.

In this paper, the problem of routing imaging drones is discussed by considering the sensitivity and quality of images recorded by drones with the aim of reducing the total imaging time of the desired area, as the objective of the problem. Also, wind as an environmental factor affecting the movement of drones is investigated by considering the uncertainty in determining its speed. Finally, the problem model is solved using GAMS software. The results indicate an optimal schedule for the monitoring system of the desired area.

For future research, the use of metaheuristic algorithms is recommended to accelerate the solution time and also to expand the dimensions of the problem.

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Data Availability

The data used in this study are available from the corresponding author upon reasonable request.

References

[1] Zhen, L., Li, M., Laporte, G., & Wang, W. (2019). A vehicle routing problem arising in unmanned aerial monitoring. *Computers & operations research*, *105*, 1–11. https://doi.org/10.1016/j.cor.2019.01.001

[2] Ristorto, G., D'Incalci, P., Gallo, R., Mazzetto, F., & Guglieri, G. (2017). Mission planning for the estimation of the field coverage of unmanned aerial systems in monitoring mission in precision farming. *Chemical engineering transactions*, *58*, 649–654. https://doi.org/10.3303/CET1758109

[3] Merino, L., Caballero, F., Martínez-de Dios, J. R., Ferruz, J., & Ollero, A. (2006). A cooperative perception system for multiple UAVs: Application to automatic detection of forest fires. *Journal of field robotics*, *23*(3–4), 165–184. https://doi.org/10.1002/rob.20108

[4] Alotaibi, K. A., Rosenberger, J. M., Mattingly, S. P., Punugu, R. K., & Visoldilokpun, S. (2018). Unmanned aerial vehicle routing in the presence of threats. *Computers & industrial engineering*, *115*, 190–205. https://doi.org/10.1016/j.cie.2017.10.030

[5] Ramirez-Atencia, C., Bello-Orgaz, G., R-Moreno, M. D., & Camacho, D. (2017). Solving complex multi-UAV mission planning problems using multi-objective genetic algorithms. *Soft computing*, *21*(17), 4883–4900. https://doi.org/10.1007/s00500-016-2376-7

[6] Mohsan, S. A. H., Othman, N. Q. H., Li, Y., Alsharif, M. H., & Khan, M. A. (2023). Unmanned aerial vehicles (UAVs): Practical aspects, applications, open challenges, security issues, and future trends. *Intelligent service robotics*, *16*(1), 109–137. https://doi.org/10.1007/s11370-022-00452-4

[7] Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management science*, *6*(1), 80–91. https://doi.org/10.1287/mnsc.6.1.80

[8] Liang, J., Zhong, H., Wang, Y., Chen, Y., Zeng, J., & Mao, J. (2023). Adaptive force tracking impedance control for aerial interaction in uncertain contact environment using barrier function. *IEEE transactions on automation science and engineering*, *21*(3), 4720–4731. https://doi.org/10.1109/TASE.2023.3301023

[9] Carvajal, C. P., Andaluz, V. H., Roberti, F., & Carelli, R. (2023). Path-following control for aerial manipulators robots with priority on energy saving. *Control engineering practice*, *131*, 105401. https://doi.org/10.1016/j.conengprac.2022.105401

[10] Han, Y., Li, J., Liu, Z., Liu, C., & Tian, J. (2020). Metaheuristic algorithm for solving the multi-objective vehicle routing problem with time window and drones. *International journal of advanced robotic systems*, *17*(2), 1729881420920031. https://doi.org/10.1177/1729881420920031

[11] Thibbotuwawa, A., Bocewicz, G., Radzki, G., Nielsen, P., & Banaszak, Z. (2020). UAV mission planning resistant to weather uncertainty. *Sensors*, *20*(2), 515. https://doi.org/10.3390/s20020515

[12] Sanjari-Parizi, M., Pouralihasani, H., & Meymand, A. Z. (2024). Multi-objective optimization for combined ground and aerial delivery systems using drones. In *international conference on industrial and systems engineering*. https://www.researchgate.net/publication/394195466_Multi-objective_optimization_for_combined_ground_and_aerial_delivery_systems_using_drones

[13] Hayat, S., Yanmaz, E., Bettstetter, C., & Brown, T. X. (2020). Multi-objective drone path planning for search and rescue with quality-of-service requirements. *Autonomous robots*, *44*(7), 1183–1198. https://doi.org/10.1007/s10514-020-09926-9

[14] Yuan, S., Ota, K., Dong, M., & Zhao, J. (2022). A path planning method with perception optimization based on sky scanning for UAVs. *Sensors*, *22*(3), 891. https://doi.org/10.3390/s22030891

[15] Huang, Y., & Hammad, A. (2024). Simulation-based optimization of path planning for camera-equipped uavs that considers the location and time of construction activities. *Remote sensing*, *16*(13), 2445. https://doi.org/10.3390/rs16132445

[16] Chang, B., Hwang, B., Lim, W., Kim, H., Kang, W., Park, Y. S., & Ko, D. W. (2025). Enhancing wildlife detection using thermal imaging drones: Designing the flight path. *Drones*, *9*(1), 52. https://doi.org/10.3390/drones9010052