https://doi.org/10.1016/j.aei.2021.101277

Unmanned Aerial Vehicle Based Low Carbon Monitoring Planning

Wen Yi[a], Monty Sutrisna[a], Shuaian Wang[b]

[a]*School of Engineering and Advanced Technology, College of Sciences, Massey University, Auckland, New Zealand*

[b]*Department of Logistics and Maritime Studies, The Hong Kong Polytechnic University, Hung Hom, Hong Kong*

Abstract: Instead of physically visiting all locations of concern by manpower, unmanned aerial vehicles (UAVs) equipped with cameras are a low-cost low-carbon alternative to carry out monitoring tasks. When a UAV flies to conduct monitoring tasks, it does not have to fly at a fixed speed; instead, it should fly at lower speeds over objects of higher concerns and vice versa. This paper addresses the UAV planning problem with a focus on optimizing the speed profile. We propose an infinite-dimensional optimization model for the problem and transform the model into an elegant linear programming formulation based on characteristics of the problem. Finally, we conduct a case study to demonstrate the effectiveness of the proposed model and the efficiency of the proposed solution method.

Keywords: unmanned aerial vehicle; low-carbon logistics; scheduling; infinite-dimensional optimization

1 INTRODUCTION

Traditionally, there are two methods to monitor an area. The first one is monitoring by patrol agents. This method is very flexible and easy to implement. However, it has two significant drawbacks. The first drawback is that some areas are difficult to access or dangerous, limiting the applicability of monitoring by patrol agents. Another problem is the high manpower costs of safety specialists, especially in developed countries. The second method to monitor is to use video cameras, e.g., at the entrance of residential buildings and at metro stations. Using video cameras can reduce the manpower costs, as a person in a central control room can monitor the scenes in several cameras at the same time. Moreover, video cameras can conduct monitoring tasks on a 24/7 basis. A shortcoming of using video cameras is that the locations of video cameras are fixed. Even though some video cameras can rotate and shoot in many directions, they can still only monitor a limited area of a construction site. It is practically impossible to install so many cameras that all corners of a construction site are monitored. By contrast, patrol agents can monitor a much larger area, though not on a 24/7 basis. Another drawback of using video cameras is that they can effectively work only with sufficient light in the monitored area.

In recent years, using unmanned aerial vehicles (UAVs) that carry video cameras to carry out monitoring tasks integrates the advantages of the above two approaches (Otto et al., 2018). UAVs equipped with cameras can provide a bird-view of locations and acquire image data efficiently, and thus are able to monitor a large area with low manpower costs. Due to these advantages, UAVs, as a low-cost low-carbon alternative to carry out monitoring tasks, have been used in a number of applications. When a natural disaster occurs, UAVs can be used to monitor the affected area and obtain data on the extent of damage (Pi et al., 2020). UAVs can patrol land borders and shorelines between two countries (Kim and Lim, 2018). In agriculture, UAVs can inspect farm conditions for soil and yield analysis (Puri et al., 2017). In build environment, UAVs equipped with infrared imaging are used to monitor the heat transfer of building blocks (Rakha, and Gorodetsky, 2018). In this study, we will develop models to plan a UAV for carrying out monitoring tasks.

1.1 Literature review

A building block in UAV routing is obtaining the flying time between two points. Li et al. (2018a) examined a three-dimensional UAV path planning problem in which a UAV travels from one point to another point in an indoor environment while keeping a certain distance from obstacles. They developed A*-based algorithms to identify the shortest path and the path whose height above the floor and stairs is minimized.

Some researchers have concentrated on optimizing UAV routes for monitoring a set of nodes, arcs, or an area. In the category on node monitoring, Kim and Lim (2018) proposed a UAV border monitoring concept in which electrification line systems to wirelessly charge drones are deployed. Drones must visit a sequence of nodes considering battery capacity constraints. A mixed-integer linear programming model is developed to determine the locations to install the electrification line systems. Zhen et al. (2019) investigated a routing problem in which UAVs monitor a set of nodes with different accuracy requirements, and in which the height at which a UAV visits each node is optimized as it affects the accuracy level of monitoring. A tabu search metaheuristic approach is developed for the problem. Xia et al. (2019) examined the routing of a fleet of UAVs for monitoring air emissions from a set of vessels (nodes). Different from many routing studies, the vessels are moving rather than standing still. A space-time network model is developed to formulate the problem, which is solved by a Lagrangian relaxation-based method.

In some situation UAVs monitor not nodes, but arcs, such as road segments, power transmission lines, and territorial borders. Chow (2016) and Li et al. (2018b) have studied the routing of a fleet of UAVs to monitor vehicle traffic on a set of road segments (arcs) over multiple periods. The problem is formulated as a mixed-integer linear program and solved by approximate dynamic programming in Chow (2016) and a local branching algorithm in Li et al. (2018b). Campbell et al. (2018) pointed out that an arc can be monitored by more than one UAV because UAVs can travel directly between any two points.

Some studies have examined the routing of UAVs to monitor an area. Yang et al. (2018) studied the design of a UAV route to monitor a target area with the aim of minimizing the total flying distance. They divided the area into discrete squares, whose side length is small enough to ensure a UAV can monitor a whole square when it flies along its center line. A modified ant colony optimization algorithm is developed to design the UAV route that passes all the discrete squares. Wang et al. (2018) examined the routing of UAVs to monitor disjoint areas over an extended time horizon, in which each area is divided into a number of cells and must be revisited within a time period. The problem is solved by a multiobjective evolutionary algorithm.

UAV monitoring planning is also related to the locations of airbases. Vural et al. (2019) considered the problem of determining the locations of airbases of UAVs that are used for surveillance. The functioning of the airbases depends on the weather conditions, which are random by nature. They developed a two-stage stochastic integer linear program to determine the locations of airbases considering uncertainty.

Given that UAVs have very limited flying time and distance, vehicles are used to transport and launch UAVs, improving the overall efficiency. Carlsson and Song (2018) examined the coordination between a truck and a UAV. Hu et al. (2019) proposed a vehicle-assisted multiple-drone routing problem and designed a heuristic solution approach.

In the above studies, the flying speed of the UAVs is assumed known and constant. We complement these studies by focusing on optimizing the speed of a UAV.

1.2 Objectives and contributions

The objective of this research is to propose a model for planning the speed of a UAV to ensure effective monitoring. We consider a UAV that flies along a fixed path and optimize the flying speed of the UAV. The flying speed of the UAV is optimized to ensure that the UAV spends the most time monitoring important segments on the path, subject to constraints that the UAV completes the path without depleting its battery. The contribution of the paper is that we propose an infinite-dimensional optimization model for the problem and transform the model into an elegant linear programming formulation based on characteristics of the problem. The effectiveness of the model is evaluated by numerical experiments.

The remainder of the paper is organized as follows: Section 2 describes the problem and formulates an infinite-dimensional optimization model. Section 3 proposes a tailored solution method. Section 4 reports the results of a case study. Conclusions are presented in Section 5.

2 PROBLEM DESCRIPTION AND OPTIMIZATION MODEL

A UAV flies along a fixed path to monitor an area of interest. We use Figure 1 to illustrate an area of a construction site and use Figure 2 to illustrate the fixed path. The length of the path is L (m), where the starting and ending points are both the depot of the UAV.

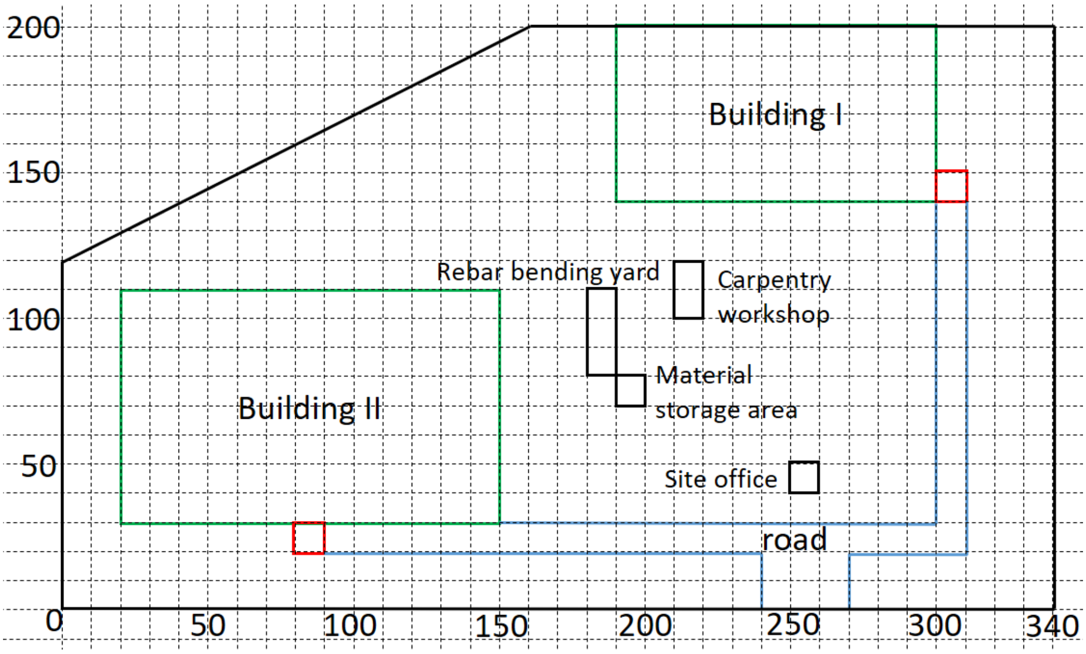

Fig. 1 Layout of a construction site

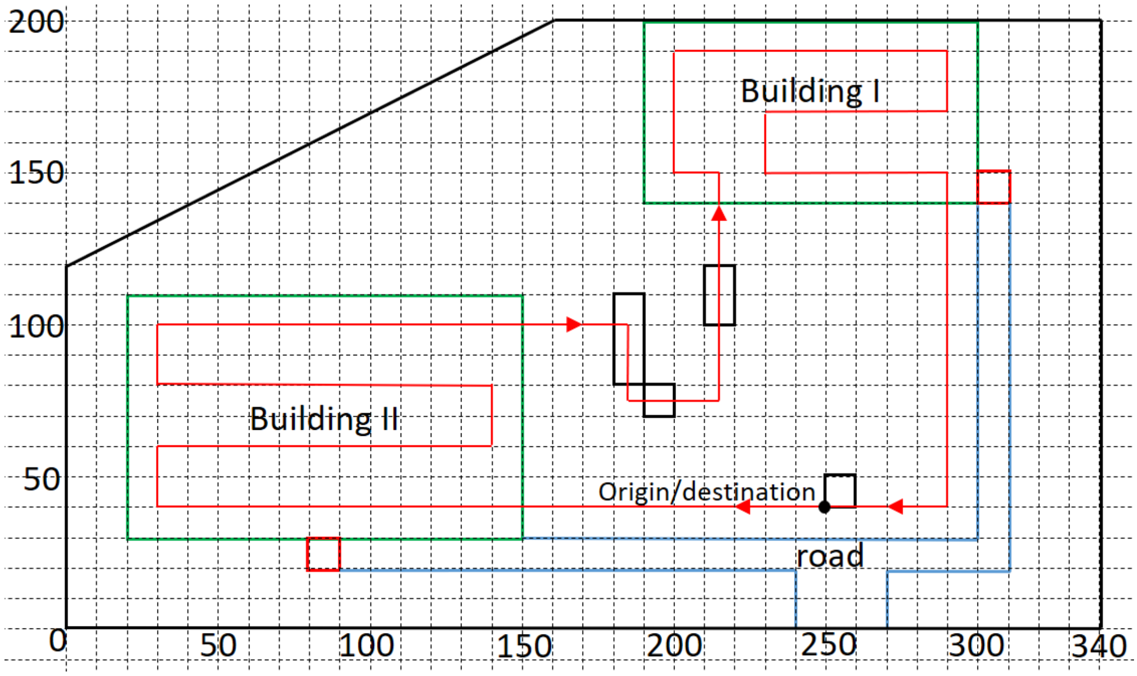

Fig. 2 Flying path of the UAV

The UAV must complete the monitoring tasks along the path in time T (s). The minimum flying speed of the UAV is $V^{\min}$ (m/s) and the maximum flying speed is

$V^{\max}$ (m/s). The battery of the UAV has an energy capacity of Q (kWh) and the energy consumption per meter (kWh/m) when the UAV flies at the speed v (m/s) is denoted by $F(v)$, $V^{\min} \leq v \leq V^{\max}$. Table 1 shows the flying duration and flying distance of a type of UAV named "DJI P4 PRO" at different speeds. It can be seen that $F(v)$ is smaller when v is larger.

Table 1 Information on the UAV DJI P4 PRO (Steiner, 2017)

Flying speed (km/h)	Flying duration (min)	Flying distance (km)
5	28	2.3
10	27.5	4.6
15	27	6.8
20	25.5	8.5
25	24	10.0
30	23	11.5
35	22	12.8
40	20	13.3

We denote by y the location on the path that is y (m) away from the origin of the path. Therefore, the UAV flies from the location $y = 0$ to the location $y = L$. The UAV can monitor an area with the radius of r (m). That is, when the UAV is at location y, $0 \leq y \leq L$, it can monitor the area from location $y - r$ to location $y + r$. Note that in reality $r \ll L$ and hence we do not need to worry about cases when $y - r < 0$ or $y + r > L$.

A location y is monitored when the UAV flies from location $y - r$ to location $y + r$. Some locations require long duration of surveillance, for example, locations where workers are conducting dangerous tasks in a construction site, and some locations require minimum surveillance, for example, site offices. Therefore, we define $g(y)$ as the minimum percentage of time in the T seconds during which location y must be monitored, $0 \le y \le L$. $g(y)$ is specified by site managers and the value of $g(y)$ at location y is determined by the flying speed of the UAV from $y - r$ to $y + r$.

Denote by function $v(y)$ (m/s) the speed function of the UAV that is to be determined. Represent by $h(y)$ the percentage of time location y is monitored; $h(y) = \frac{1}{T}\int_{y-r}^{y+r} \frac{1}{v(x)} dx$, $0 \le y \le L$. It is required that $h(y) \ge g(y)$. We maximize $\int_0^L g(x)(h(x) - g(x))dx$. In plain words, we maximize the extra surveillance effect beyond the minimum requirement, that is, $h(x) - g(x)$, weighted by the importance of the locations, that is, $g(x)$, $0 \le x \le L$.

The UAV monitoring planning problem with decision functions $v(y)$ and $h(y)$ can be formulated as follows:

[P1] max $\int_0^L g(x)(h(x) - g(x))dx$ (1)

subject to

$$h(y) = \frac{1}{T}\int_{y-r}^{y+r} \frac{1}{v(x)} dx, 0 \le y \le L \quad (2)$$

$$h(y) \ge g(y), 0 \le y \le L \quad (3)$$

$$\int_0^L \frac{1}{v(x)} dx \le T \quad (4)$$

$$\int_0^L F(v(x))dx \le Q \quad (5)$$

$$V^{\min} \le v(y) \le V^{\max}, 0 \le y \le L. \quad (6)$$

The objective function (1) maximizes the extra monitoring effect beyond the minimum requirement weighted by the importance of the locations. Constraint (2) calculates the percentage of time each location is monitored. Constraint (3) enforces the minimum percentage of monitoring time for each location. Constraint (4) requires the UAV to complete the path in time T. Constraint (5) mandates that the energy consumption for the UAV to complete the path is at most Q. Constraint (6) specifies the lower and upper bounds of the flying speeds on the path.

3 SOLUTION METHOD

Model [P1] is challenging to solve because its decisions are not scalars or vectors but functions. In other words, model [P1] is an infinite-dimensional optimization problem. Moreover, there are integration operations in the objective function (1) and constraints (2), (4), and (5), which all add to the complexity of the problem. To address the challenges, we examine the properties of the problem and develop a tailored solution method based on these properties.

3.1 Reformulation

First, the speed decision $v(y)$ appears in the denominator in constraints (2) and (4), posing difficulty for the problem. We therefore define $t(y) \coloneqq \frac{1}{v(y)}$ as the new decision function in place of $v(y)$, meaning the flying time (s) per meter at location y, $0 \leq y \leq L$. We further define $f(t(y)) \coloneqq F(1/t(y))$ as the energy consumption per meter (kWh/m) of the UAV when flying at the speed $1/t(y)$. Then, constraints (2), (4), (5), and (6) are replaced by the following ones, respectively:

$$h(y) = \frac{1}{T}\int_{y-r}^{y+r} t(x)dx\,, 0 \leq y \leq L \tag{7}$$

$$\int_0^L t(x)dx \leq T \tag{8}$$

$$\int_0^L f(t(x))dx \leq Q \tag{9}$$

$$\frac{1}{V^{\max}} \leq t(y) \leq \frac{1}{V^{\min}}, 0 \leq y \leq L. \tag{10}$$

Second, since $r \ll L$ and a UAV cannot suddenly dramatically change its speed, $t(x)$ will not change much over $y - r \leq x \leq y + r$. Therefore, constraint (7) can be approximated by

$$h(y) \approx \frac{1}{T}\int_{y-r}^{y+r} t(y)dx = \frac{2r}{T}t(y), 0 \leq y \leq L. \tag{11}$$

Embedding Eq. (11) into constraint (3), we have

$$t(y) \geq \frac{T}{2r}g(y), 0 \leq y \leq L. \tag{12}$$

Combining constraints (10) and (12), we have

$$\max\{\frac{1}{V^{\max}}, \frac{T}{2r}g(y)\} \leq t(y) \leq \frac{1}{V^{\min}}, 0 \leq y \leq L. \tag{13}$$

We embed Eq. (11) into the objective function (1) and obtain a new objective function with decision function $t(y)$:

$$\text{[P2]}\ \max \int_0^L g(x)[\frac{2r}{T}t(x) - g(x)]dx \tag{14}$$

subject to constraints (8), (9), and (13).

Model [P2] looks nicer than model [P1] (He, 2016; Tan et al., 2019); however, [P2] is still an infinite-dimensional optimization problem.

3.2 Discretization

In reality, the function $g(y)$ should be a piecewise constant function. For instance, when the UAV flies from the origin to Building II in Figure 2, the function $g(y)$ should be the same constant value; when the UAV flies within the area of Building II, the function $g(y)$ should be another constant value (we can, of course, divide Building II into different parts and allow $g(y)$ to have different values for different parts of Building II). Therefore, we rewrite $g(y)$ as the following form:

$$g(y) = g_k, l_{k-1} \leq y \leq l_k, k = 1, \dots, K \tag{15}$$

where K is the number of segments that the path is divided into, l_k is a given parameter, $k = 0,1, \dots, K$, $l_0 = 0$ and $l_K = L$. For example, the path in Figure 2 is divided into $K = 11$ segments in Figure 3.

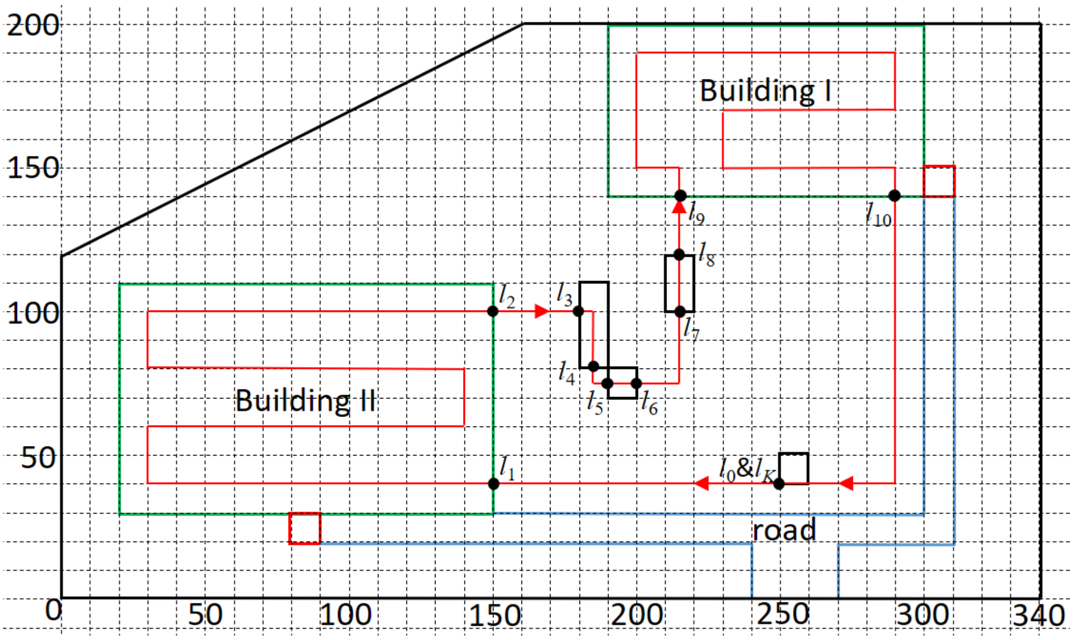

Fig. 3 Divide the path into 11 segments

Once the path is divided into K segments, a natural question is: is the optimal speed (equivalently, the optimal $t(y)$) on each segment a constant value or not? To answer this question, we examine the flying data DJI P4 PRO shown in Table 1. Because we are concerned with the relation between $t(y)$ (the time required to fly for 1 m) and $f(t(y))$ (the amount of energy used to fly for 1 m at the speed $1/t(y)$), we plot the relation in Figure 4 based on the data in Table 1. Note that in Figure 4, the vertical axis is the $f(t(y))/Q$, that is, the proportion of the total energy capacity of the battery used to fly for 1 m at the speed $1/t(y)$. In Figure 4, when $t(y) = 0.12$, that is, the speed is 8.33 m/s, or equivalently, 30 km/h, $f(t(y))/Q = 0.00073$. Figure 4 evidently shows that

Property 1: $f(t(y))$ is a convex function of $t(y)$.

Based on Property 1, we immediately have

Theorem 1: The optimal $t(y)$, denoted by $t^*(y)$, is a piecewise constant function and can be represented by

$$t^*(y) = t_k^*, l_{k-1} \leq y \leq l_k, k = 1, \dots, K. \tag{16}$$

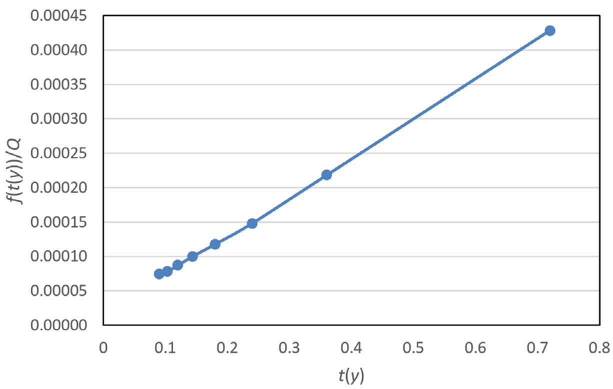

Fig. 4 Relation between $t(y)$ and $f(t(y))$

Based on Theorem 1, model [P2] is equivalent to the following discretized model with decision variables $t_k, k = 1, \ldots, K$:

$$[\text{P3}] \max \sum_{k=1}^{K} g_k (l_k - l_{k-1})(\frac{2r}{T} t_k - g_k) \tag{17}$$

subject to

$$\sum_{k=1}^{K} (l_k - l_{k-1}) t_k \leq T \tag{18}$$

$$\sum_{k=1}^{K} (l_k - l_{k-1}) f(t_k) \leq Q \tag{19}$$

$$\max\{\frac{1}{V^{\max}}, \frac{T}{2r} g_k\} \leq t_k \leq \frac{1}{V^{\min}}, k = 1, \ldots, K. \tag{20}$$

Model [P3] is no longer an infinite-dimensional optimization problem. It has only K decision variables. A challenge of solving model [P3] is that constraint (19) is nonlinear as the function $f(t(y))$ is generally nonlinear.

3.3 Linearization

As mentioned in Property 1, $f(t(y))$ is a convex function of $t(y)$. The functional form for $f(t(y))$ cannot be derived analytically but has to be estimated numerically. We use a piecewise linear function to estimate $f(t(y))$ by connecting all the available data, as shown in Figure 4. Mathematically, denote by (t^θ, f^θ) the set of data available, $\theta = 1, \ldots, \Theta$. We then estimate $f(t(y))$ as

$$f(t(y)) = \max_{\theta=1,\ldots,\Theta-1} [\frac{f^{\theta+1} - f^\theta}{t^{\theta+1} - t^\theta} (t(y) - t^\theta) + f^\theta]. \tag{21}$$

Since $f(t(y))$ is estimated as a piecewise linear convex function, we can linearize constraint (19) by introducing decision variables u_k, $k = 1, \dots, K$, and replace the nonlinear constraint (19) by the following three groups of linear constraints:

$$\sum_{k=1}^{K} (l_k - l_{k-1}) u_k \leq Q \tag{22}$$

$$u_k \geq \frac{f^{\theta+1} - f^{\theta}}{t^{\theta+1} - t^{\theta}} (t_k - t^{\theta}) + f^{\theta}, \theta = 1, \dots, \Theta - 1, k = 1, \dots, K \tag{23}$$

$$u_k \geq 0, k = 1, \dots, K. \tag{24}$$

where u_k is the energy consumption per meter (kWh/m) when the UAV flies on segment $k = 1, \dots, K$.

We thus have a linear programming model [P4] with objective function (17) and constraints (18), (20), (22), (23), and (24). Model [P4] can be solved by off-the-shelf solvers (Yan et al., 2011; He et al., 2020).

4 COMPUTATIONAL EXPERIMENTS

We carry out a case study to demonstrate the applicability of the proposed model and algorithm. The layout of the construction site is shown in Figure 1, the path of the UAV is shown in Figure 2, and the path is divided into 11 segments, as shown in Figure 3. The lengths of the 11 segments are shown in Table 2. Segments 2, 4, 6, 8, and 10 correspond to Building II, rebar bending yard, material storage area, carpentry workshop, and Building I, respectively. Therefore, these five segments require surveillance by UAV and their minimum percentage of time to be monitored g_k is also shown in Table 2.

Table 2 Information of the 11 segments on the path

Segment	Length	g_k	Note
1	100	0.00	
2	520	0.01	Building II
3	30	0.00	
4	20	0.05	Rebar bending
5	10	0.00	
6	10	0.01	Storage
7	40	0.00	
8	20	0.04	Carpentry
9	20	0.00	
10	325	0.01	Building I
11	140	0.00	

The UAV is a DJI P4 PRO whose flying parameters are shown in Table 1 and Figure 4. The other parameters of the UAV are $r = 10$, $V^{\min} = 1$, and $V^{\max} = 40$. The UAV needs to complete the path in $T = 180$ seconds. The linear programming model [P4] is solved using CPLEX 12.6.3 on a PC equipped with 3.60GHz of Intel Core i7 CPU and 16GB of RAM.

The case is solved to optimality in 0.01s. The optimal objective value is 0.6475. In the optimal solution, the total flying time (i.e., the left-hand side of constraint (18)) is exactly 180s.

The optimal solutions of t_k and u_k are shown in Table 3. We can see from Table 3 that the solution has a clear structure. Since segment 4 has the largest value of g_k (i.e., segment 4 is the most important), the flying speed on it is the lowest (1 km/h). Then, segment 8 is the second most important and the UAV also flies at a low speed on it. The UAV flies at the highest speed on the other segments.

Table 3 Optimal solution

Segment	Optimal t_k (s)	Optimal flying speed (km/h)	Optimal u_k
1	0.09	40	0.0001
2	0.09	40	0.0001
3	0.09	40	0.0001
4	3.26	1	0.0019
5	0.09	40	0.0001
6	0.09	40	0.0001
7	0.09	40	0.0001
8	0.36	10	0.0002
9	0.09	40	0.0001
10	0.09	40	0.0001
11	0.09	40	0.0001

We further plot the flying-time–flying-distance curve in Figure 5. It can be seen that the UAV spends long time on segment 4. The slopes of the curve, which correspond to the flying speeds, are equal except those on segment 4 and segment 8.

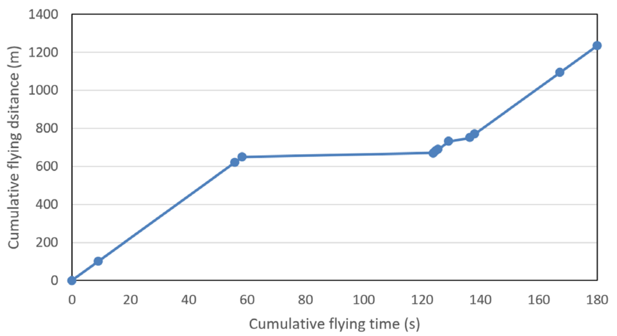

Fig. 5 Relation between cumulative flying time and cumulative flying distance

The flying-time–energy-consumption curve is plotted in Figure 6. It can be seen that the slopes of the curve, which correspond to the power consumption rates (i.e., energy consumption per unit time), are equal except those on segment 4 and segment 8. Note that although the power consumptions per meter on segment 4 and segment 8 are higher than those on the other segments because of the lower speeds on segment 4 and segment 8, the power consumptions per second on segment 4 and segment 8 are lower than those on the other segments, as shown in Figure 6.

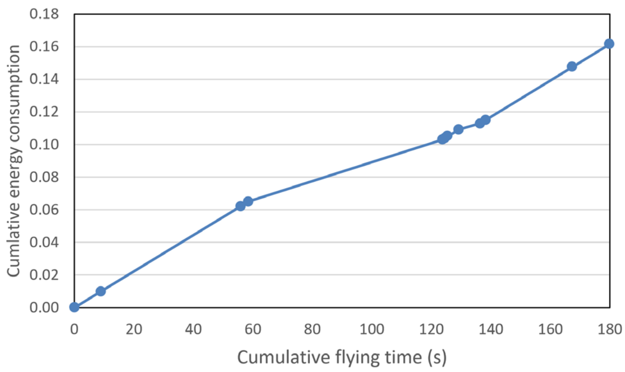

Fig. 6 Relation between cumulative flying time and cumulative energy consumption

5 CONCLUSIONS

This study has proposed a UAV monitoring planning problem in which a UAV flies on a fixed path. The flying speed of the UAV is optimized to ensure that the UAV spends the most time monitoring important segments of the path while ensuring that the UAV completes the path within a certain time and without depleting its battery. We propose an infinite-dimensional optimization model for the problem and transform the model into an elegant linear programming formulation based on characteristics of the problem. A case study is carried out to demonstrate the applicability of the proposed UAV scheduling model. In general, the UAV flies at low speeds on important segments of the path and at its highest speeds on less-important segments.

ACKNOWLEDGMENT

This study is supported by Massey University Research Fund (MURF) RM20721.

REFERENCES

Campbell, J. F., Corberán, Á., Plana, I., & Sanchis, J. M. (2018). Drone arc routing problems. Networks, 72(4), 543-559.

Carlsson, J. G., & Song, S. (2018). Coordinated logistics with a truck and a drone. Management Science, 64(9), 4052-4069.

Chow, J. Y. (2016). Dynamic UAV-based traffic monitoring under uncertainty as a stochastic arc-inventory routing policy. International Journal of Transportation Science and Technology, 5(3), 167-185.

He, J. (2016). Berth allocation and quay crane assignment in a container terminal for the trade-off between time-saving and energy-saving. Advanced Engineering Informatics, 30(3), 390-405.

He, J., Tan, C., Yan, W., Huang, W., Liu, M., & Yu, H. (2020). Two-stage stochastic programming model for generating container yard template under uncertainty and traffic congestion. Advanced Engineering Informatics, 43, 101032.

Hu, M., Liu, W., Peng, K., Ma, X., Cheng, W., Liu, J., & Li, B. (2018). Joint routing and scheduling for vehicle-assisted multidrone surveillance. IEEE Internet of Things Journal, 6(2), 1781-1790.

Kim, S. J., & Lim, G. J. (2018). Drone-aided border surveillance with an electrification line battery charging system. Journal of Intelligent & Robotic Systems, 92(3-4), 657-670.

Li, F., Zlatanova, S., Koopman, M., Bai, X., & Diakité, A. (2018a). Universal path planning for an indoor drone. Automation in Construction, 95, 275-283.

Li, M., Zhen, L., Wang, S., Lv, W., & Qu, X. (2018b). Unmanned aerial vehicle scheduling problem for traffic monitoring. Computers & Industrial Engineering, 122, 15-23.

Otto, A., Agatz, N., Campbell, J., Golden, B., & Pesch, E. (2018). Optimization approaches for civil applications of unmanned aerial vehicles (UAVs) or aerial drones: A survey. Networks, 72(4), 411-458.

Pi, Y., Nath, N. D., & Behzadan, A. H. (2020). Convolutional neural networks for object detection in aerial imagery for disaster response and recovery. Advanced Engineering Informatics, 43, 101009.

Puri, V., Nayyar, A., & Raja, L. (2017). Agriculture drones: A modern breakthrough in precision agriculture. Journal of Statistics and Management Systems, 20(4), 507-518.

Rakha, T., & Gorodetsky, A. (2018). Review of Unmanned Aerial System (UAS) applications in the built environment: Towards automated building inspection procedures using drones. Automation in Construction, 93, 252-264.

Steiner, E., 2017. Drone flight stats. https://airdata.com/blog/2017/UAV-flight-stats-part-1. Accessed 21 Jun 2020.

Tan, C., He, J., & Yu, H. (2019). Mathematical modeling of yard template regeneration for multiple container terminals. Advanced Engineering Informatics, 40, 58-68.

Vural, D., Dell, R. F., & Kose, E. (2019). Locating unmanned aircraft systems for multiple missions under different weather conditions. Operational Research, 1-20.

Wang, Y., Kirubarajan, T., Tharmarasa, R., Jassemi-Zargani, R., & Kashyap, N. (2018). Multiperiod coverage path planning and scheduling for airborne surveillance. IEEE Transactions on Aerospace and Electronic Systems, 54(5), 2257-2273.

Xia, J., Wang, K., & Wang, S. (2019). Drone scheduling to monitor vessels in emission control areas. Transportation Research Part B: Methodological, 119, 174-196.

Yan, W., Huang, Y., Chang, D., & He, J. (2011). An investigation into knowledge-based yard crane scheduling for container terminals. Advanced Engineering Informatics, 25(3), 462-471.

Yang, C. H., Tsai, M. H., Kang, S. C., & Hung, C. Y. (2018). UAV path planning method for digital terrain model reconstruction–A debris fan example. Automation in Construction, 93, 214-230.

Zhen, L., Li, M., Laporte, G., & Wang, W. (2019). A vehicle routing problem arising in unmanned aerial monitoring. Computers & Operations Research, 105, 1-11.