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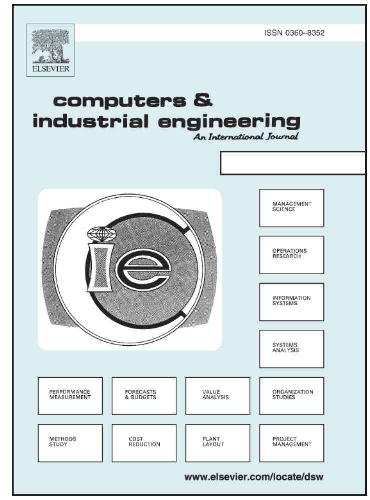

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Unmanned Aerial Vehicle Scheduling Problem for Traffic Monitoring

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Unmanned Aerial Vehicle Scheduling Problem for Traffic Monitoring

Abstract: For more accurate multiple-period real-time monitoring of road traffic, this paper investigates the unmanned aerial vehicle scheduling problem with uncertain demands. A mixed integer programming model is designed for this problem by combining the capacitated arc routing problem with the inventory routing problem. A local branching based solution method is developed to solve the model. A case study which applies this model to the road traffic in Shanghai is performed. In addition, numerical experiments are conducted to validate the effectiveness of the proposed model and the efficiency of the proposed solution method.

Keywords: UAV routing problem, CARP with time window, Inventory routing problem, Traffic monitoring

1. Introduction

With the rapid propulsion of urbanization and the surge in car ownership in recent years, the contradiction of urban traffic supply and demand turns worse, which results the corresponding traffic congestion and traffic safety issues. As of 2016, car ownership in China

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had reached 285 million. According to China Highway Network, a vertical website of China Highway Academy, which focuses on information communication and service in the construction, management and planning of Chinese highways, 15 of the major cities with more than one million citizens lost nearly 10 billion China Yuan per day due to traffic congestion and management problems in China. Traffic jams are rather common in many cities in China. Beijing, Shanghai and other large cities are becoming 'blocked' cities. An adverse road condition renders the car the most time-consuming mode of travel; this trend is spreading to second- and third-tier cities in China.

How to prevent various types of traffic problems using reasonable method is the focus of this study. Road traffic information is the basis for the implementation of traffic planning and traffic control. Existing urban road traffic monitoring devices, such as vehicle induction loops, traffic cameras and infrared monitors, can collect required traffic flow and speed data. As traffic inspection equipment are not installed on a number of express roads, primary arterial roads, secondary arterial roads and other road segments, traffic information cannot always be obtained. Unmanned aerial vehicles (UAVs), which are commonly known as drones, constitute a new type of monitoring equipment. Equipped with different imaging sensors, UAVs can capture target images, and the monitored images can be transmitted in real time to a control station via a wireless transmission system. Recent developments in aviation, microelectronics, computers, navigation, communications, sensors and other related technologies have yielded continuous improvements in the performance of UAVs. Information collection is one of the most important applications of UAVs (Xia et al., 2017) and has been extensively employed in meteorological exploration, disaster monitoring, geological surveys, environmental monitoring, avalanche detection and other fields. The use of UAVs as a mean of collecting traffic data offers numerous advantages, such as the capacity to observe wide areas (covering 300 to 500 square meters at a height of 150 to 300 meters), low cost, excellent flexibility, high efficiency and real-time operations (Harwin and Lucieer, 2012).

In this paper, UAVs serve as a traditional traffic monitor auxiliary or supplementary method for collecting road traffic information. In this vein, given a fleet of UAVs and monitoring requirements, it is critical to optimize the routing of UAVs in multiple periods in order to minimize operating costs. The remainder of this paper is organized as follows: Section 2 reviews related works; Section 3 elaborates on the problem background; and the model is formulated in Section 4. Local branching based solution methods are developed in Section 5. The numerical experiments are illustrated in Section 6, and the conclusions are presented in the last section.

2. Related works

UAV-related studies have become a popular research topic in recent years. Salvo et al. (2014) presented a method to appraise actual traffic flow situations in urban areas using UAVs to achieve accurate traffic research. Guerriero et al. (2014) proposed a distributed system of autonomous UAVs and presented a mathematical formulation of the problem as a multi-criteria optimization model based on a vehicle routing problem with soft time window (VRPTW) constraints, in which the total distances travelled by the UAVs, the customer satisfaction and the number of UAVs were simultaneously considered to solve distributed dynamic scheduling problems. Murray et al. (2015) provided two mixed integer linear programming formulations that were aimed at the optimal routing and scheduling of unmanned aircraft and delivery trucks to solve last-mile delivery in logistics operations. A typical vehicle routing problem (VRP) was introduced to discuss how a UAV cooperates with a typical delivery vehicle to distribute parcels in the scenario. Cho et al. (2015) designed a mathematical model based on the VRP for UAV-aided security operations in the oil and gas industry. They stated that UAVs can collect information about possible emergencies. The main goal of their model was to create an optimal operational schedule of UAVs to satisfy the monitoring needs in each time period by considering the minutely calculating the charging cost and operating cost. Yakıcı (2016) addressed the problem of locating and routing of UAVs at the tactical level and formulated this problem as an integer linear program with the objective of maximizing the total score obtained from visited demand points by flight routes of UAVs. They also developed a novel ant colony optimization metaheuristic that can find the best objective value in a short time.

However, the monitoring demands were considered as nodes in the network in the above studies. As mobile sensors, UAVs are more suitable for monitoring demand arcs than demand nodes because they can monitor objects during flight (Chow, 2016). Although UAVs can arbitrarily travel in the air and are not limited to a particular network, flying over an unknown space may cause UAVs to experience unknown obstacles. In the deployment of UAVs, therefore, monitoring based on demand arcs is meaningful. Related studies are primarily reviewed from the perspective of the arc routing problem. The Chinese postman problem (CPP) presented by Mei-Ko (1962) was representative of the basic arc routing optimization problem. Golden and Wong (1981) proposed the capacitated arc routing problem (CARP) and modelled it as a mixed integer programming problem. The CARP attracted significant attention because it can be used to solve many real-life problems. Thus, many scholars have performed substantial modelling analysis, some of which have been employed in specific applications. For example, Eglese and Li (1992) designed a simulated annealing approach to solve the problem of deicing in Lancashire; Li and Eglese (1996) investigated how to design routes for gritters to minimize costs and considered multiple depot locations, limited vehicle capacities and roads with different priorities for gritting. To make the CARP consistent with an actual situation, many researchers added restrictions based on the specific case at hand or combined it with other variants. Lacomme et al. (2005) proposed that trips must be planned over a multi-period horizon in many applications and identified a new problem that they called periodic CARP (PCARP). Monroy et al. (2013) introduced the PCARP with irregular services. The problem consisted of determining a set of routes to cover a given network within a period of time. They proposed a mathematical model and a heuristic solution method. Salazar-Aguilar et al. (2013) introduced the synchronous arc and node routing problem, which was inspired by the practical application of road marking operations. The purpose of their problem was to determine the routes and schedules of the painting and supply vehicles in road marking operations to minimize the completion time of pavement marking. Lopes et al. (2014) proposed the location-arc routing problem (LARP) and considered scenarios in which the requirement related to the borders in the network rather than the nodes in the network. Riquelme-Rodríguez et al. (2016) minimized the routing costs and penalty costs due to the lack of humidity in roads by comparing two methods for locating water depots along a road network. Their problem can be considered as a variant of PCARP from the perspective of the work of spraying water for dusting suppression as described in the problem.

Although multi-period extensions have been involved in the CARP, some scholars adopted a frequency variable (i.e., visiting an arc every t periods). In our research, we formulate UAV scheduling problem for traffic monitoring to an inventory-based CARP model. Related studies are reviewed from the perspective of the inventory routing problem. Beltrami and Bodin (1974) explored how to invest the least number of vehicles to solve the problem of garbage removal in New York and Washington from a long-term perspective. Russell and Igo (1979) introduced a transport strategy for distribution to a customer within a day and within a week to achieve efficient transportation. Federgruen and Zipkin (1984) were the first researchers to propose an integrated inventory and vehicle routing problem (IIVRP). Golden et al. (1984) conducted a similar study and described the urgency of demands by the ratio of the current inventory level to the inventory capacity; then, a heuristic algorithm was designed to solve this problem. Recently, Li et al. (2014) considered an IRP for a large petroleum enterprise group. In their paper, they focused on avoiding stock out for any station rather than transportation cost minimization. They presented a tabu search algorithm and Lagrangian relaxation technique to address the problem. Schuijbroek et al. (2017) analysed the primary operational cost of bike sharing systems, in which bikes were rebalanced over time to provide users with a reasonable number of bikes and open docks. They determined the service level demands at each bike sharing station and designed the optimal vehicle routes for rebalancing the inventory. Azadeh et al. (2017) presented a model of the IRP with transshipment in the presence of perishable product. Vehicle routing and inventory decisions were simultaneously made over the planning horizon to satisfy customer’s demand in a maximum level policy. They proposed a genetic algorithm based approach to solve the problem and used a numerical example to illustrate the validity of the model.

The research contribution is threefold. First, considering that uncertain monitoring demands are distributed on arcs, the CARP is introduced to solve the UAV traffic flow monitoring problem. Second, we combine the CARP and the IRP to formulate UAV monitoring traffic flow in multiple periods as a mixed integer linear programming. Third, since commercial integer linear programming solvers such as CPLEX can obtain optimal solutions within reasonable time only for small-scale instances of the problem. We have therefore developed a local branching based solution to solve large-scale instances within relatively short computing times.

3. Problem description

The problem in this study relates to dynamically allocating a fleet of UAVs to a traffic network for monitoring demand arcs in multiple periods. Figure 1 shows the main process of using UAVs for road traffic monitoring. First, the locations and number of road sections are determined to be monitored and use them as monitoring tasks for UAVs. Then, these monitoring tasks are entered in control platform in order to assign which routes each UAV should monitor. Subsequently, airborne high-definition cameras monitor the road traffic conditions during flight, and the monitoring video can be transmitted in real time to the UAV base station via a wireless transmission system. Finally, control personnel extract the traffic information from the video and report the results to the drivers who are travelling on the corresponding road in real time to assist them in making informed decisions in selecting driving routes.

(Insert Figure 1 here)

Figure 1: Aerial monitoring of an unmanned aerial vehicle

The basic CARP problem is depicted in Figure 2. In a network, each monitoring demand is represented by an arc. Each arc has a cost, and parts of the arcs hold the service demand. Each UAV tour must start and end at the same depot. The problem aims to minimize the total operating costs while satisfying the UAV capacity constraints. In reality, traffic accidents occur on a road during one period may cause a significant increase in monitoring demand of the relevant arc in a network over the next few periods. Therefore, real-time traffic data should be collected more frequently to prevent the accidents. Traditional frequency-based method that is monitoring demand arcs every t period is not time-dependent, while the inventory-based method is time-dependent. We consider UAVs' monitoring as a kind of service products, and over-frequent monitoring as inventory holding. This paper handles the proposed problem using the CARP & IRP model. In addition, current commercial UAVs can run within half an hour (Chow. 2016). Thus, research on allocating UAVs in multiple time periods is meaningful.

(Insert Figure 2 here)

Figure 2: A simplified case of CARP and CARP & IRP

For this problem, an important decision is how to allocate UAVs to minimize the total cost of the monitoring process. The deployment of more UAVs to more arcs will increase costs, but additional monitoring demands can be continuously satisfied to reduce the risk of non-monitoring. The challenges embedded in this decision problem contain the following aspects. Each UAV monitor several demand arcs, and each arc is served by several UAVs. The many-to-many mapping relationships among the arcs and capacity limit of each UAV produce many challenges in the model formulation for this problem. Besides, from the perspective of each monitoring arc, their demands are uncertain and may be related to the density of traffic flow throughout whole day. For real-time traffic monitoring, arc routing problems must be addressed in multiple periods of inventory adjustment.

4. Model formulation

This section formulates a mixed integer programming model for UAV scheduling in traffic monitoring. The CARP model of Golden and Wong (1981) is modified to adapt to the background of UAVs monitoring traffic. Further, we extend the problem to multiple periods. Limited battery capacity will affect the flight endurance of UAVs, which may affect their monitoring capability. As most UAVs that are suitable for traffic flow monitoring are battery-powered, relevant factors of battery energy are considered in the model.

4.1 Notions

Indices and sets:

$G(N,E)$ network with a set of vertices N, $i,j \in N, i \neq j, N = \{0,1,\cdots,|N|\}$; a set of undirected arcs E, $(i,j) \in E$.

i,j,p index of vertices; 0 denotes the depot.

(i,j) index of monitoring demand arcs.

k index of UAVs.

K set of all UAVs, $K = \{1,2 \cdots, k, \cdots, |K|\}$.

t index of monitoring periods; 0 denotes the initial period.

T set of all monitoring periods, $T = \{0,1 \cdots, t, \cdots, |T|\}$.

Parameters:

c_{ij} required electricity (in units of cost) for traversing arc $(i,j) \in E$.

$c_{i,j}^{a}$ required additional electricity (in units of cost) for monitoring arc $(i,j) \in E$.

$d_{i,j}$ equals one if there is a link between vertex $i \in N$ and $j \in N$; otherwise, equals zero.

$\bar{Q}_k$ battery capacity of UAV k.

$h_{i,j}$ inventory holding cost of frequently monitoring arc $(i,j) \in E$ per period.

f_k unit charging cost of the UAV k.

$q_{i,j,t}$ increase demand which is unmet for monitoring arc $(i,j) \in E$ at period t.

$\bar{S}_{i,j}$ maximum 'monitoring satisfaction' of arc $(i,j) \in E$ per period.

M a sufficiently large positive number.

Decision variables:

$\gamma_{i,j,k,t}$ a binary variable; equals one if arc $(i,j) \in E$ is traversed by UAV k at period t.

$\theta_{i,j,k,t}$ a binary variable; equals one if arc $(i,j) \in E$ is served by UAV k at period t.

$\sigma_{i,j,k,t}$ a flow variable; eliminates sub-tours.

$\tau_{i,j,t}$ 'monitoring satisfaction' of arc $(i,j) \in E$ at period t.

$\alpha_{k,t}$ a binary variable; equals one if UAV k is charged at period t.

$\beta_{k,t}$ charging quantity of UAV k at period t.

$\delta_{k,t}$ battery level of UAV k at the period t.

4.2 Mathematical model

$$Minimize\ \ Z = \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} \sum_{t \in T} c_{ij}\, \gamma_{i,j,k,t} + \sum_{i \in N} \sum_{j \in N} \sum_{t \in T} h_{i,j} \tau_{i,j,t} + \sum_{k \in K} \sum_{t \in T} f_k \beta_{k,t} \quad (1)$$

$$s.t.\quad \sum_{p \in N} \gamma_{p,i,k,t} - \sum_{p \in N} \gamma_{i,p,k,t} = 0 \qquad \forall i \in N, k \in K, t \in T \quad (2)$$

$$\sum_{k \in K} \left(\theta_{i,j,k,t} + \theta_{j,i,k,t}\right) \leq 1 \qquad \forall (i,j) \in E, t \in T \quad (3)$$

$$d_{i,j} \geq \gamma_{i,j,k,t} \qquad \forall (i,j) \in E, k \in K, t \in T \quad (4)$$

$$\gamma_{i,j,k,t} \geq \theta_{i,j,k,t} \qquad \forall (i,j) \in E, k \in K, t \in T \tag{5}$$

$$\sum_{i \in N} \sum_{j \in N} \left(c_{ij}\gamma_{i,j,k,t} + c^a_{i,j}\theta_{i,j,k,t} \right) \leq \delta_{k,t} \qquad \forall k \in K, t \in T \tag{6}$$

$$\sum_{p \in N} \sigma_{i,p,k,t} - \sum_{p \in N} \sigma_{p,i,k,t} = \sum_{j \in N} \theta_{i,j,k,t} \qquad \forall i \in N \backslash \{0\}, k \in K, t \in T \tag{7}$$

$$\sigma_{i,j,k,t} \leq |N|^2 \gamma_{i,j,k,t} \qquad \forall (i,j) \in E, k \in K, t \in T \tag{8}$$

$$\tau_{i,j,t-1} \geq q_{i,j,t} + \tau_{i,j,t} - M \sum_{k \in K} \left(\theta_{i,j,k,t} + \theta_{j,i,k,t} \right) \qquad \forall (i,j) \in E, t \in T \backslash \{0\} \tag{9}$$

$$\tau_{i,j,t-1} \leq q_{i,j,t} + \tau_{i,j,t} + M \sum_{k \in K} \left(\theta_{i,j,k,t} + \theta_{j,i,k,t} \right) \qquad \forall (i,j) \in E, t \in T \backslash \{0\} \tag{10}$$

$$\tau_{i,j,t} \geq \bar{S}_{i,j} - M\left(1 - \sum_{k \in K} \left(\theta_{i,j,k,t} + \theta_{j,i,k,t} \right)\right) \qquad \forall (i,j) \in E, t \in T \tag{11}$$

$$\gamma_{0,j,k,t} \leq M\left(1 - \alpha_{k,t}\right) \qquad \forall k \in K, t \in T, j \in N \backslash \{0\} \tag{12}$$

$$\delta_{k,0} = \bar{Q}_k \qquad \forall k \in K \tag{13}$$

$$\delta_{k,t} = \delta_{k,t-1} - \sum_{i \in N} \sum_{j \in N} \left(c_{ij}\gamma_{i,j,k,t-1} + c^a_{i,j}\theta_{i,j,k,t-1} \right) + \beta_{k,t-1} \qquad \forall k \in K, t \in T \backslash \{0\} \tag{14}$$

$$\beta_{k,t} \leq M\alpha_{k,t} \qquad \forall k \in K, t \in T \tag{15}$$

$$q_{i,j,t} \leq \tau_{i,j,t} \leq \bar{S}_{i,j} \qquad \forall (i,j) \in E, t \in T \tag{16}$$

$$0 \leq \delta_{k,t} \leq \bar{Q}_k \qquad \forall k \in K, t \in T \tag{17}$$

$$\gamma_{i,j,k,t} \in \{0,1\} \qquad \forall (i,j) \in E, k \in K, t \in T \tag{18}$$

$$\theta_{i,j,k,t} \in \{0,1\} \qquad \forall (i,j) \in E, k \in K, t \in T \tag{19}$$

$$\alpha_{k,t} \in \{0,1\} \qquad \forall (i,j) \in E, k \in K, t \in T \tag{20}$$

$$\sigma_{i,j,k,t} \geq 0 \qquad \forall (i,j) \in E, k \in K, t \in T \tag{21}$$

$$\tau_{i,j,t} \geq 0 \qquad \forall (i,j) \in E, t \in T \tag{22}$$

$$\beta_{k,t} \geq 0 \qquad \forall k \in K, t \in T \tag{23}$$

$$\delta_{k,t} \geq 0 \qquad \forall k \in K, t \in T \tag{24}$$

Objective (1) is divided into three minimizing terms: the traversing cost, the inventory holding cost and the battery charging cost. Constraints (2) are the flow conservation constraints. Constraints (3) impose that each arc with monitoring demand will be served by the UAV exactly once during one period. Constraints (4) ensure that arc (i,j) can be traversed only if there is a link between vertex i and j. Constraints (5) ensure that arc (i,j) can be served only if UAV k traverse it. Constraints (6) specify that the traversing electricity consumption and the monitoring electricity consumption of each UAV cannot exceed its battery level per period. Constraints (7) and (8) eliminate illegal sub-tours. Constraints (9)-(11) ensure that 'monitoring satisfaction degree' of each arc either decreases in the next period if it is not monitored by UAVs during one period or reaches to the maximum 'monitoring satisfaction degree' if it is monitored by UAVs in one period. Constraints (12) impose that UAVs cannot monitor arcs when it is charging. Constraints (13) ensure that battery level is equal to battery capacity of each UAV in the initial period. Constraints (14) are the electricity conservation constraints. Constraints (15) indicate that if UAV k is not charged, the charging quantity is zero in period t. Constraints (16) state the upper and lower bounds for the 'monitoring satisfaction degree'. Constraints (17) state the upper and lower bounds for the battery level. Constraints (18)-(24) assure nonnegativity and integrality of the corresponding decision variables.

5. Algorithmic strategies

The mathematical model presented in Section 4 can be immediately solved by the CPLEX solver for small-scale problem instances. However, for other large-scale instances, the model is too intractable to be directly solved by the CPLEX. Thus, the local branching based method is considered to solve the formulated model.

5.1 Basic definitions

To conveniently describe the local branching strategy, we need to define the notations involved in the algorithm, as shown in Table 1.

Table 1: Notations of the local branching based solution method

(Insert Table 1 here)

5.2 Local branching based solution method

The core idea of the local branching strategy is to use the CPLEX solver as a black-box 'tactical' tool to explore appropriate solution subspaces, which are defined and controlled at a 'strategic' level by a simple external branching framework. In the spirit of classical local search meta-heuristics, the neighbourhoods of this solution strategy are obtained by introducing linear inequalities termed local branching cuts (Fischetti and Lodi, 2003).

The proposed model is a mixed integer programming model, including two sets of binary variables $\gamma_{i,j,k,t}$ and $\theta_{i,j,k,t}$. The decision variables $\theta_{i,j,k,t}$ is closely related to $\gamma_{i,j,k,t}$; thus only the set of binary variables $\gamma_{i,j,k,t}$ has a significant impact on searching the solution space and limiting the solving speed. The main framework of the local branching procedure is illustrated as follows:

Step 1: Construct an initial solution γ^0 according to the binary variables $\{\gamma_{i,j,k,t}|\}$ that are obtained by solving the proposed mathematical model without local branching cuts. Its objective value is denoted by $fitness(\gamma^0)$.

Step 2: Set the iteration number to $n = 1$. Derive the left-branch and the right-branch from γ^0 according to the constraints $|\gamma - \gamma^{n-1}| \leq u$ and $|\gamma - \gamma^{n-1}| \geq u + 1$, respectively.

Step 3: Explore the incumbent solution γ^n in the solution space, which consists of the constraints $|\gamma - \gamma^{n-1}| \leq u$ (the left-branch of γ^{n-1}).

Step 4: Update the incumbent optimal solution γ^n and its objective value $fitness(\gamma^n)$ in the iteration n; the solution space should be updated in each iteration by different mechanisms $\boldsymbol{Strategy}\,(m)$; $n \leftarrow n + 1$. Details of the mechanisms $\boldsymbol{Strategy}\,(m)$ will be subsequently addressed.

Step 5: If the iteration number reaches the preset maximum value $iter\_max$ or the times of unimproved objective value reaches the preset value $without\_imp$, stop. $\gamma^* \leftarrow \gamma^n$, $best\_obj \leftarrow fitness(\gamma^n)$.

In ***Step 4***, the mechanisms $\boldsymbol{Strategy}\,(m)$ are critical to the entire local branching based solution method. A total scheme of the mechanisms $\boldsymbol{Strategy}\,(m)$ is represented by the pseudo-code in Algorithm 1 and Algorithm 2.

Two different cases exist in the updating process. The first case involves obtaining an improved solution; the second case involves obtaining an unimproved solution. For these two cases, the handling strategies are illustrated in Algorithm 1. For the former case, the solution process is continued according to ***Step 4*** of the local branching procedure; for the latter case, we enlarge the current solution space by increasing the neighbourhood size.

Algorithm 1 Basic scheme of the mechanisms $\boldsymbol{Strategy}\,(m)$

if $\gamma^n < \gamma^*$ **then**
$\gamma^* \leftarrow \gamma^n,\ best\_obj \leftarrow fitness(\gamma^n)$;
update the solution space by the left-branch of γ^n ($|\gamma - \gamma^n| \leq u$) and the right-branches of all found solutions;
else
update the solution space by the left-branch of γ^n ($|\gamma - \gamma^n| \leq u + \lceil u/2 \rceil$) and the right-branches of all found solutions;
endif

Algorithm 2 Enhanced scheme of the mechanisms $\boldsymbol{Strategy}\,(m)$

if $elapsed\_time \geq time\_limit$ **then**
if $\gamma^n < \gamma^*$ **then**
$\gamma^* \leftarrow \gamma^n,\ best\_obj \leftarrow fitness(\gamma^n)$;
update the solution space by the left-branch of γ^n ($|\gamma - \gamma^n| \leq u$) and the right-branches of all found solutions except γ^{n-1};
Else
update the solution space by the left-branch of γ^n ($|\gamma - \gamma^n| \leq \lfloor u/2 \rfloor$) and the right-branches of all found solutions;
endif
endif

The left-branch reflects the radius of γ^n's neighbourhood in the solution spaces of $\gamma_{i,j,k,t}$. In some cases, the left-branch can be time-consuming for the value of the parameter u. Therefore, a time limit is imposed on the left-branch computation. Two different cases exist once the time limit is exceeded. An enhanced scheme of the mechanisms $\boldsymbol{Strategy}\,(m)$ is introduced to handle these two cases, which are detailed in Algorithm 2. If the incumbent solution has been improved, the right-branch of γ^{n-1} ($|\gamma - \gamma^{n-1}| \geq u + 1$) should be replaced by the right-branch of γ^n ($|\gamma - \gamma^n| \geq u + 1$) in the new solution space as the time limit for exploring the solution γ^n is reached; otherwise, we reduce the size of the neighbourhood to accelerate the solving process.

6. Model application and experiments

In this section, the proposed models and solution algorithms are applied to a practical problem of traffic flow monitoring in Shanghai, China. Some numerical experiments are conducted on a PC (Intel Core i5, 1.70 GHz; Memory, 8 G) by CPLEX 12.6.1 (Visual Studio 2015, C#) to validate the feasibility of the proposed model and the effectiveness of the solution method.

6.1 Problem background

(Insert Figure 3 here)

Figure 3: Road traffic situations in Shanghai

The model application was implemented in a traffic network of Shanghai, China. Shanghai, which is representative of large cities in China. Traffic congestion varies from one period to another. According to actual situations in Shanghai, morning and evening peak periods usually range from 7:30 am ~ 9:30 am and from 16:30 pm ~ 18:30 pm. In these two time periods, the traffic flow of the entire network is extremely large with a large area of congestion. From 12:00 pm ~ 14:00 pm on work days, the traffic flow of the entire network is relatively large with significant local area congestion. The different time periods of Shanghai traffic congestion are shown in Figure 3. The traffic congestion is divided into four levels: red represents 'Blocked', yellow denotes 'Crowded', light green represents 'Smooth', and green denotes 'Unblocked'. These levels of traffic congestion are based on a large amount of actual traffic history data, which are used to set parameters in all experiments of the rest parts of Section 6.

6.2 Testing for 'monitoring satisfaction degree'

We compare values of 'monitoring satisfaction degree' (i.e., $\tau_{i,j,t}$) obtained by the proposed inventory-based method and by traditional frequency-based method using the instance in Figure 4. In this instance, the number of UAVs is set to three and the number of periods is set to 12; some of the parameters are randomly generated, as shown in Table 2. Note that the value of $\tau_{i,j,0}$ is same in the initial period of two methods. The results are shown in Figures 5 and 6.

Table 2: Parameters setting of Section 6.2

(Insert Table 2 here)

(Insert Figure 4 here)

Figure 4: Illustrative network of Section 6.2

(Insert Figure 5 here)

Figure 5: Value of $\tau_{i,j,t}$ obtained by the proposed inventory-based method

(Insert Figure 6 here)

Figure 6: Value of $\tau_{i,j,t}$ obtained by traditional frequency-based method

From Figures 5 and 6, we can observe that the proposed inventory-based method can satisfy monitoring demands of arcs in each period through the way of consuming 'monitoring satisfaction degree' and inventory restocking. However, traditional frequency-based cannot respond to variant monitoring demands which are changing with periods. Monitoring demand arcs by UAVs according to a certain periodic interval is not time-dependent, so monitoring status is either excessive monitoring or inadequate monitoring, which will result in high monitoring costs and large frequency of traffic accident.

6.3 Sensitivity test of algorithm parameters

Prior to verifying the effectiveness of the algorithm, some parameters in the proposed method should be determined. u is a critical parameter to control the neighbourhood size for solving each node during the branching process. The time limits for solving each node by the CPLEX solver also need to be set to a proper value.

Table 3: Computation time for different parameter settings

(Insert Table 3 here)

Some experiments are conducted to explore the influence of these parameter settings on the computation time of the solution results, as illustrated in Table 3. The number of iterations in the local branching is set to 100. The entire solution procedure terminates if the incumbent best objective value does not improve after 100 consecutive iterations.

(Insert Figure 7 here)

Figure 7: Computation time of the proposed method for different parameter settings

The results in Figure 7 are intuitive: the value of parameter u and the time limit for each node are not positively and negatively related to the computation time. Figure 7 indicates that setting u to 25 and setting the time limit on each node to 40 seconds is appropriate for this problem. Therefore, we set this value of neighbourhood size and time limit for experiments of Section 6.4.

6.4 Experiments using the proposed solution method

The following numerical experiments on small- and large-scale instances are performed by applying both CPLEX and local branching. The solution obtained by CPLEX is used for the comparison. Observing these results in Tables 4 and 5, we can find that for small-scale instances, CPLEX can obtain the optimal solutions. For 13 of 18 small-scale instances, the feasible solutions obtained by the proposed solution method are same as the optimal solutions generated by CPLEX, whereas, the proposed solution method takes less computation time. On large-scale instances where CPLEX cannot obtain feasible solutions, our solution method can provide feasible solutions within three hours. In addition, the average gap between the results obtained by the proposed solution method and the optimal result is approximately 0.370%, which indicates that the results are accurate.

Table 4: Comparison between the proposed method and the CPLEX for small-scale problems

(Insert Table 4 here)

Table 5: Comparison between the proposed method and the CPLEX for large-scale problems

(Insert Table 5 here)

To sum up, the above observations can indicate that the proposed solution method is appropriate for solving the formulated model and has a definite advantage in computation time. It can be a good trade-off between solutions and computation time.

7. Conclusions

This study proposes a mixed integer programming model for traffic monitoring, which optimizes the decisions of UAV scheduling with the objective of minimizing the total expected costs of operation for uncertain monitoring demands. Some advances and contributions of this study are as follows:

(1) The UAVs are introduced as a supplementary means of urban road traffic inspection equipment to improve the accuracy of traffic monitoring. As mobile sensors, UAVs are more suitable for monitoring demand arcs than demand nodes. In the deployment of UAVs, monitoring based on demand arcs is considered in this paper. The focus of most studies is the demand node.

(2) The proposed UAVs route planning optimization model combines the basic model of the CARP and the IRP, which is time-dependent, hence provides a framework for multiple-period real-time traffic monitoring by UAVs. Most related studies did not consider this problem. This paper includes an explorative study of this new problem for specific backgrounds.

(3) The proposed local branching based method has excellent solution efficiency. Especially when the scale of the problem is expanded, local branching can search for a better solution in a shorter calculation time and approximate the exact solution. This strategy provides an effective decision-making method for solving the UAV scheduling problem.

However, this study has limitations. For example, the traffic information collected by UAVs can be used to assist and supplement ground fixed traffic monitors. The effective integration of information from both methods warrants additional research. The local branching based solution method is a heuristic method in nature. The design of an exact solution method for solving large-scale problems remains a challenging task for future studies. These limitations will form the research directions for our future studies.

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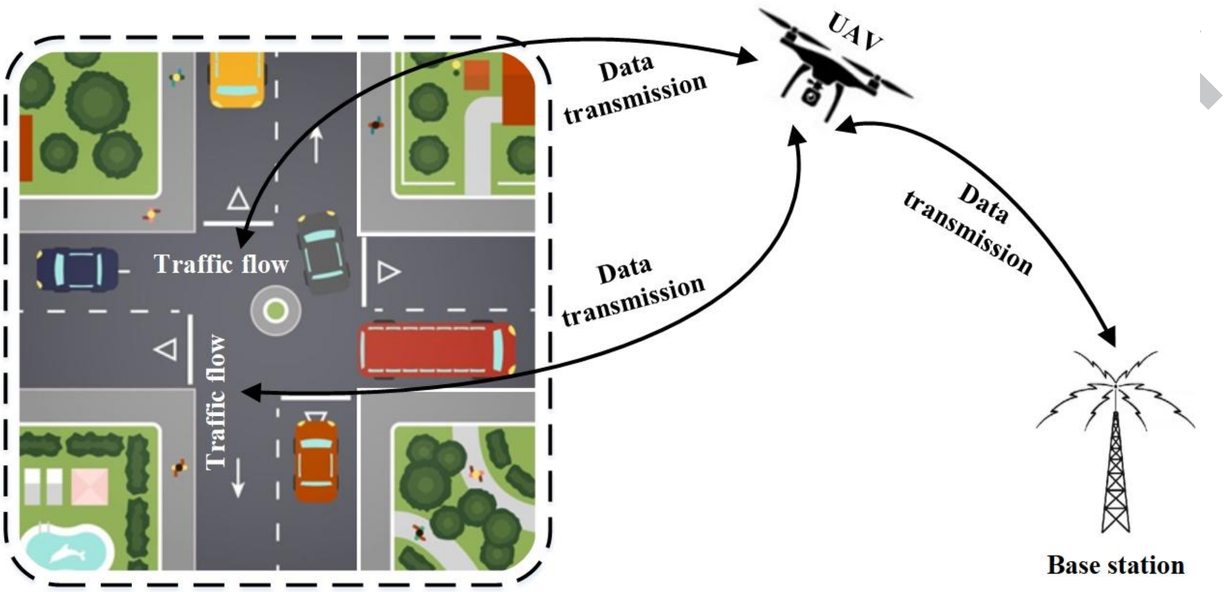

Figure 1: Aerial monitoring of an unmanned aerial vehicle

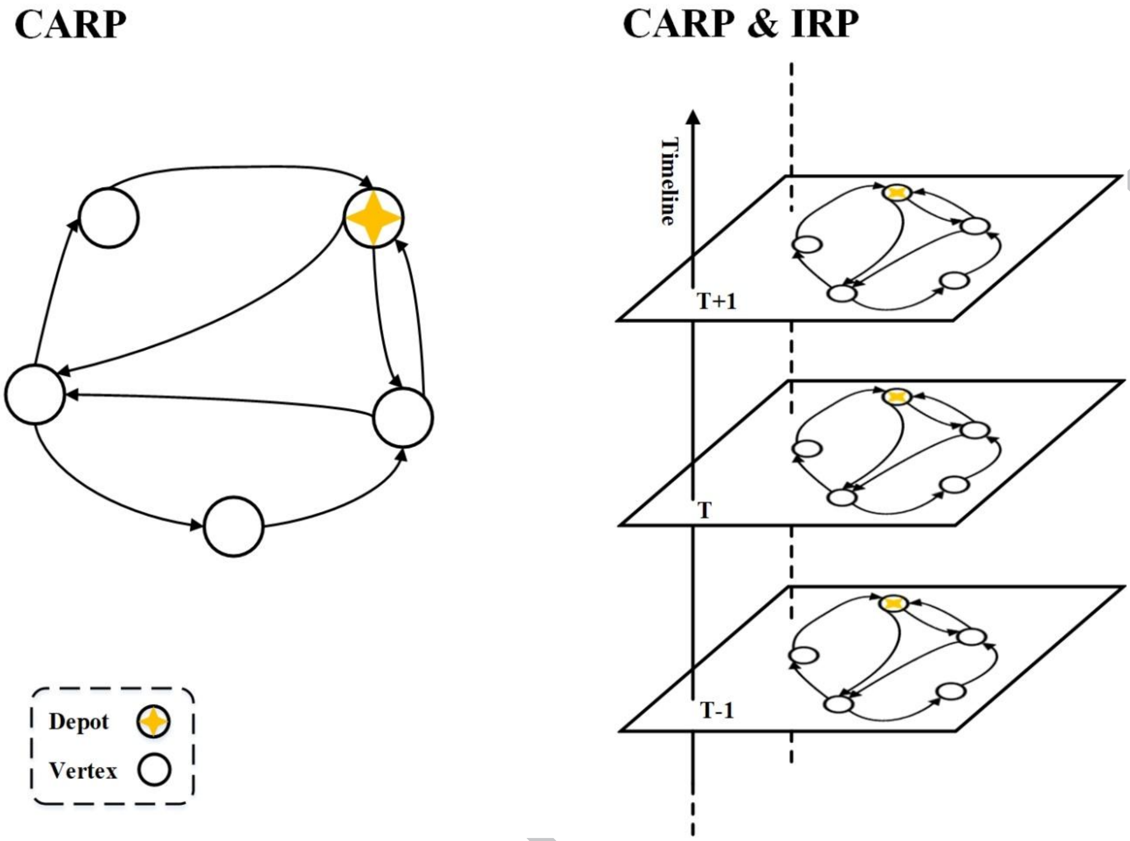

Figure 2: A simplified case of CARP and CARP & IRP

Morning and evening peak hours every day

12:00 pm ~ 14:00 pm on weekdays

Figure 3: Road traffic situations in Shanghai

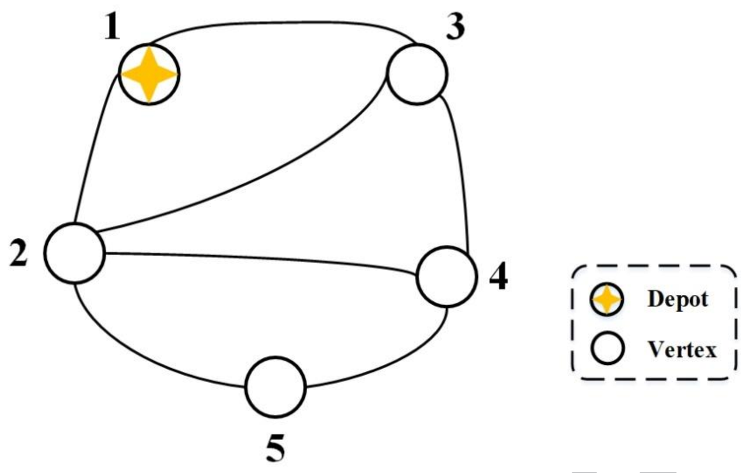

Figure 4: Illustrative network of Section 6.2

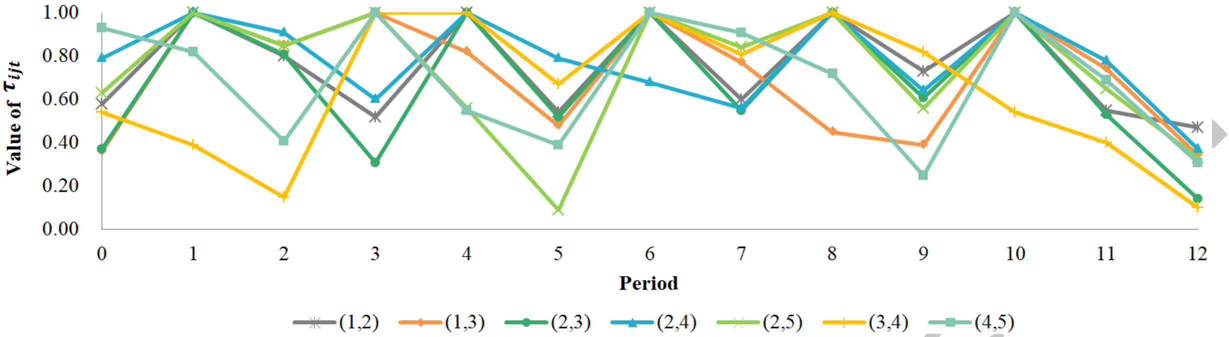

Figure 5: Value of $\tau_{i,j,t}$ obtained by the proposed inventory-based method

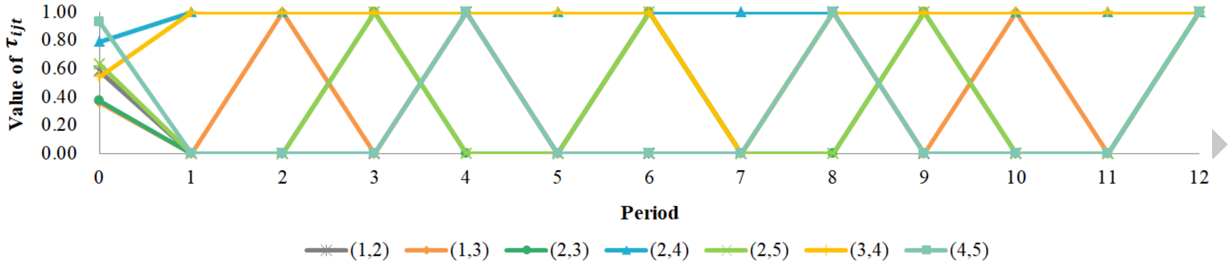

Figure 6: Value of $\tau_{i,j,t}$ obtained by traditional frequency-based method

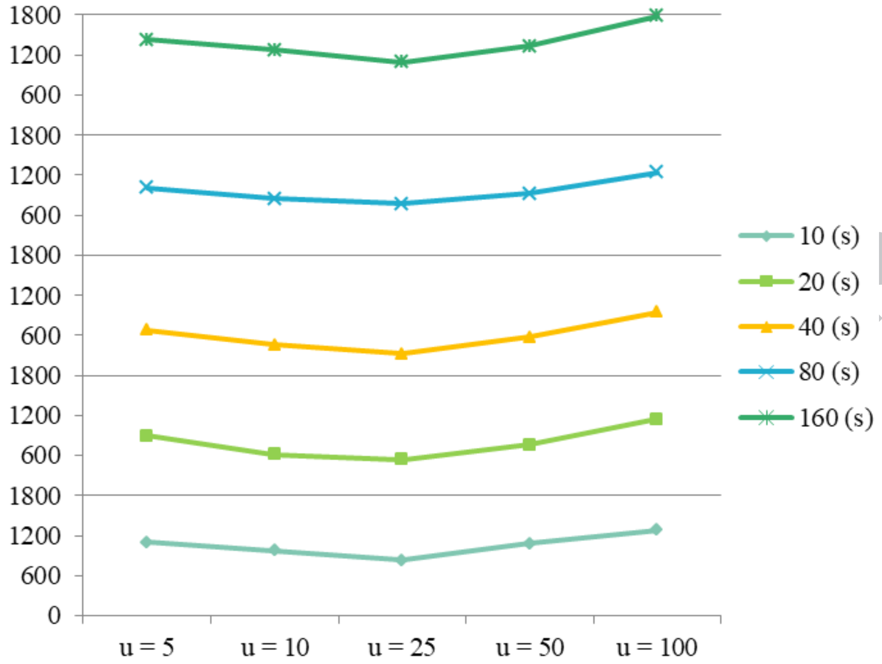

Figure 7: Computation time of the proposed method for different parameter settings

Table 1: Notations of the local branching based solution method

Notations	Explanations
γ^0	initial solution
γ^n	incumbent solution
γ^*	best known solution
$fitness$	objective values of incumbent solutions
$best\_obj$	objective value of best known solution
u	neighbourhood-size parameter
$iter\_max$	maximum number of allowed iterations
$without\_imp$	time of the unimproved objective value
$elapsed\_time$	elapsed time for exploring a new solution
$time\_limit$	time limit parameter for exploring a new solution

Table 2: Parameters setting of Section 6.2

Parameter	Distribution type	Distributions
$c_{i,j}$	$U(a,b)$	(0,10)
$r_{i,j}$	$U(a,b)$	(0.05,0.5)
$e_{i,j}$	$U(a,b)$	(0,8)
f_k	$U(a,b)$	(2,4)
$s_{i,j,0}$	$U(a,b)$	(0.34,1)

Table 3: Computation time of the proposed method for different parameter settings

CPU Times (s)	Time Limit for Each Node				
	10 (s)	20 (s)	40 (s)	80 (s)	160 (s)
Par u = 5	1103.1	892.1	677.6	1015.7	1428.1
Par u = 10	972.6	621.4	461.3	850.0	1270.4
Par u = 25	830.3	536.1	322.7	767.8	1091.9
Par u = 50	1079.8	762.3	576.6	921.7	1329.9
Par u = 100	1284.6	1147.7	946.3	1241.0	1784.6

Table 4: Comparison between the proposed method and the CPLEX for small-scale problems

Instance ID	No. Links	CPLEX Z_{CPLEX}	CPLEX T_{CPLEX} (s)	Local branching Z_{LoBr}	Local branching T_{LoBr} (s)	Obj Gap (%)
5-2-5-1	12	48.27	2.9	48.27	2.5	0.000
5-2-5-2	10	29.80	2.7	29.80	1.9	0.000
5-2-5-3	10	59.88	1.9	59.88	3.5	0.000
5-2-5-4	10	55.39	2.7	55.39	2.4	0.000
5-2-5-5	14	44.45	2.8	44.45	2.7	0.000
5-2-5-6	6	45.94	2.6	45.94	1.2	0.000
8-2-6-1	22	197.63	15.6	197.63	20.4	0.000
8-2-6-2	26	191.18	13.8	191.18	29.8	0.000
8-2-6-3	20	263.97	68.3	263.97	142.32	0.000
8-2-6-4	26	253.21	14.1	253.21	28.8	0.000
8-2-6-5	22	107.52	22.7	107.52	62.9	0.000
8-2-6-6	20	207.44	34.5	207.44	72.5	0.000
9-3-6-1	28	388.92	1164.2	390.25	412.0	0.272
9-3-6-2	32	371.18	711.3	371.18	231.7	0.000
9-3-6-3	28	422.82	1352.6	423.92	687.7	0.260
9-3-6-4	30	434.74	1018.0	435.02	374.1	0.064
9-3-6-5	30	350.19	963.9	352.48	523.7	0.065
9-3-6-6	32	420.72	1098.9	421.96	396.1	0.281
Avg.			360.8		166.5	0.052

Notes: (1) The numbers in each case id (e.g., '5-2-5-1') denote the number of vertices (i,j) '(4,4)', the number of vehicles '2', the number of periods '3', and the index of the case '1', respectively. (1) 'Z' denotes the objective values; 'T' denotes the computation time, and the unit is seconds. (2) $GAP_{OBJ} = (Z_{LoBr} - Z_{CPLEX}) / Z_{CPLEX}$.

Table 5: Comparison between the proposed method and the CPLEX for large-scale problems

Instance ID	No. Links	CPLEX		Local branching		Obj Gap (%)	Time ratio
		Z_{CPLEX}	T_{CPLEX} (s)	Z_{LoBr}	T_{LoBr} (s)		
10-4-6-1	42	509.33	3867.1	509.33	1030.8	0.000	0.267
10-4-6-2	40	567.57	4358.5	570.78	1176.7	0.566	0.270
10-4-6-3	40	495.41	4475.0	495.54	1790.2	0.026	0.400
10-4-6-4	42	532.95	5366.3	536.77	2004.9	0.717	0.374
10-4-6-5	38	475.82	3232.6	481.39	872.8	1.171	0.270
10-4-6-6	36	525.64	4504.5	532.63	1551.6	1.330	0.344
12-4-8-1	46	613.29	7052.0	614.77	3214.7	0.241	0.456
12-4-8-2	40	592.67	5708.4	592.67	2347.9	0.000	0.411
12-4-8-3	46	508.83	6707.7	512.96	2628.5	0.812	0.392
12-4-8-4	42	621.89	5476.2	622.95	2237.5	0.170	0.409
12-4-8-5	42	593.50	6891.6	593.81	3021.2	0.052	0.438
12-4-8-6	40	541.34	6246.3	541.34	2554.6	0.000	0.409
15-5-8-1	52	N.A.	>7200.00	694.88	5415.4	-	-
15-5-8-2	50	N.A.	>7200.00	661.52	6474.5	-	-
15-5-8-3	48	N.A.	>7200.00	743.66	5621.7	-	-
15-5-8-4	50	N.A.	>7200.00	707.74	5230.6	-	-
15-5-8-5	52	N.A.	>7200.00	705.62	5821.0	-	-
15-5-8-6	50	N.A.	>7200.00	714.45	6174.8	-	-
Avg.					3287.2	0.424	0.370

Notes: (1) Time ratio=T_{LoBr}/T_{CPLEX}.

Highlights

Unmanned Aerial Vehicle Scheduling Problem for Traffic Monitoring

- This paper studies unmanned aerial vehicles scheduling problem under uncertainty.
- A mixed integer programming model is designed for this problem
- The model combines capacitated arc routing problem with inventory routing.
- A local branching based solution method is developed for solving the model.