Commanding Cooperative UGV-UAV With Nested Vehicle Routing for Emergency Resource Delivery

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I. INTRODUCTION

With the rapid development of e-commerce, express delivery, and industry intelligent unmanned system technology, the cooperation of unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) has long been used for some harshest military tasks, such as monitoring and inspection in contested urban environments and border patrolling [1], border intelligence, surveillance, reconnaissance (ISR) missions [2]–[4], and post-disaster relief [5]. It is also used in many domain, such as cellular communications, data gathering [6], urban illegal building detection [7] and map building [8]. During the epidemic diseases spreading such as COVID-19, package delivery becomes a key means of emergency resource transmission. In such situations, to prevent infectious diseases from becoming more serious, contactless delivery becomes a hot choice. However, how can we get a package and ensure personal safety? Cooperative UGV and UAV may be one applicable way to make it possible.

The contactless delivery of emergency resources is of great significance to the completion of various post-disaster operations and military missions. However, due to the complex and harsh environment in the delivery process, as well as the uncertainty of organization and command, delivery vehicles, transportation networks, the delivery of materials may not achieve the desired effect.

Emergency resource becomes scarce after disaster. The main reasons for the scarcity of resource are as follows. On the one hand, the time and scale of the disaster are difficult to predict, and it is uneconomical and unrealistic to maintain a large reserve of emergency resource. Therefore, it is often difficult to store resource to meet all the needs of disaster area. On the other hand, although resource can be mobilized through various social channels after a disaster, the suddenness of disaster and the effectiveness of the mobilization of resource are conflicts that are difficult to reconcile. Leading to a large and concentrated demand for food, medicine, tents and other materials. The existing resource of various channels may not fully cover the needs of disaster area. After large-scale natural disasters occur, it is often necessary to...
mobilize rescue equipment, tents, and bedding within the first time. There are a large number of emergency resource of various types, including food, medicine, tent, and so on. The demand for supplies in the disaster area has the characteristics of heterogeneity. According to the analysis of the actual needs for post-disaster rescue, how to quickly rationalize the limited heterogeneous supplies after the disaster occurs. Contactless delivery to disaster areas is a problem worthy of study. Since disasters often cause damage to the original roads, and large vehicles cannot pass, it is necessary to use a cooperative UGV-UAV system.

In this article, we comprehensively consider the above points to study how to allocate customers and plan the route of UGV and UAV to minimize the total service time when a UGV is equipped with a UAV to deliver to multiple customers in a certain area by a UGV-UAV delivery system as shown in Figure 1. The solution to this problem can not only meet the population isolation requirements when major public health emergencies such as COVID-19 and earthquake occur, reduce contact between people, but also increases the flexibility of traditional truck delivery of goods and improves overall delivery effectiveness.

The transparent environment makes it difficult to conceal the delivery activities, and the fire threat caused by high-tech weapon strikes reduces the safety factor of material delivery operations, resulting in poor reliability of emergency resource delivery and causing significant losses of the front requirements. Therefore, it is a very important task for unmanned systems to correctly accept the OPORD from the commander, choose a reliable delivery method, and designing an optimal route.

Recently, many scholars have conducted in-depth research on the cooperation of UGV and UAV for delivery. Although the use of UAVs in the logistics field is in its infancy, commercial practices have already begun. Amazon was the first company to propose the concept of drone delivery [9]. In 2013, Amazon proposed a drone express delivery plan called Prime Air. The goal is to provide services to customers within 16km of the warehouse. The 8-axis UAV of different models with a maximum load of 2kg can be delivered within 30 minutes as fast as possible and automatically return home. UAV owns the advantages of fast speed and low cost. In 2016, the first delivery test was completed in England. SF Express began researching drone delivery as early as 2012 and has obtained hundreds of patents. In June 2016, JD Logistics Laboratory also started drone testing. As the JD Smart Logistics National Operation-Dispatching Center and JD National UAV Operation-Dispatching Center, the UAVs delivery to some villages around was achieved during the “618” period in 2017. The Chinese logistics “three giants” JD, SF Express, and Alibaba are competing with companies from all over the world to develop UAVs with performance, endurance and reliability to deliver goods on a large scale and solve the high cost of express companies confronting the “last one-mile” puzzle.

Although UAV delivery has been practiced in enterprises, academic research on the optimization of the UAV delivery system is relatively rare. In recent years, many scholars have conducted research in this area. As a traveling salesman problem (TSP) with drone, Murray and Chu [10] first proposed the flying sidekick traveling salesman problem (FSTSP), which provided a simple mathematical formulation and heuristic solution methodology for the problem of cooperation between only one traditional transportation truck and one UAV. Dorling et al. [11] established a model with the consideration of the relationship between the flight distance and load of the UAV. This study found that energy consumption and delivery time cannot be optimized at the same time. Therefore, it is necessary to balance these two objects and choose actual scenarios. Song et al. [12] integrated the UAV logistics system’s limited flight time and the large impact of cargo on performance, and proposed a UAV transportation path model based on the programming model, and designed a heuristic algorithm to solve the path. Rabta et al. [5] considered the application of UAVs in humanitarian logistics and proposed a model that minimizes the total cost of UAV transportation items under the constraints of load and energy consumption. Sundar and Rathinam [13] proposed a mathematical model for a UAV flight control system that considers refuelling in a distribution center. In the study, a drone visits the distribution center to refuel and continues to perform its mission. However, this method can only generate a flight path for a UAV, which limits its potential applicability to real-world problems.

In this article, we address the problem of cooperative UGV-UAV for emergency resource delivery with two modules. One for the commanding of cooperative UGV-UAV from the operation order (OPORD) from the commander, which outputs the 5W (What, Who, Where, Why, and When) element from the C-BML formatted OPORD as follows: what is the task, who to perform the task, where the task should be executed, why they should be performed and when to act. Another for the nested vehicle routing, which attempts to answer the following questions: what is the UGV route, what is the task, who to perform the task, where the task should be executed, why they should be performed and when to act. Essential to UGV-UAV cooperation is the use of UA Vs in the logistics field is in its infancy, commercial practices have already begun. Amazon was the first company to propose the concept of drone delivery [9]. In 2013, Amazon proposed a drone express delivery plan called Prime Air. The goal is to provide services to customers within 16km of the warehouse. The 8-axis UAV of different models with a maximum load of 2kg can be delivered within 30 minutes as fast as possible and automatically return home. UAV owns the advantages of fast speed and low cost. In 2016, the first delivery test was completed in England. SF Express began researching drone delivery as early as 2012 and has obtained hundreds of patents. In June 2016, JD Logistics Laboratory also started drone testing. As the JD Smart Logistics National Operation-Dispatching Center and JD National UAV Operation-Dispatching Center, the UAVs delivery to some villages around was achieved during the “618” period in 2017. The Chinese logistics “three giants” JD, SF Express, and Alibaba are competing with companies from all over the world to develop UAVs with performance, endurance and reliability to deliver goods on a large scale and solve the high cost of express companies confronting the “last one-mile” puzzle.

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are the UAV sorties, and how can we split the customers for the UGV and UAV?

Our contributions can be concluded as follows:

(1) We formulate the model of cooperative UGV-UAV for emergency resource delivery.

(2) We design the intelligent task understanding module for the OPORD from the commander.

(3) We propose one three-stage method for the nested vehicle routing problem, in which we use the saving and improvement heuristics based on the “UGV First, and UAV Second” idea.

The rest of this article is organized as follows. In Section II, some related work is presented. In Section III, we provide a formal problem definition, design the intelligent task understanding module, and propose on three-stage heuristic solution methodology. In Section IV, we conducted a numerical analysis to emphasize the benefits and limitations of cooperative UGV and multiple deploying UAVs. And supplementary analysis explored the size of the area, speed and range of UAV, and energy limitation. In Section V, we summarize this article and point out further research topics.

II. LITERATURE REVIEW

A. COALITION BATTLE MANAGEMENT LANGUAGE

The design goals of Coalition Battle Management Language (C-BML) are: (1) an unambiguous command; (2) a protocol to modularize the robot. For these two goals, the first solve the problem of ambiguity, select a context-free grammar, specify its production, and then It can disambiguate grammatically. At the grammatical level of C-BML, Thomas Remmersmann et al. [14] believe that C-BML must be clear and unambiguous. In order to be clear and correct, C-BML must be designed as a formal language. A collection of sentences generated by a formal grammar [15]. In C-BML, the grammar is a command and control vocabulary grammar [16], and contains the concept of 5W. The core grammar rule is to combine tasks assigned to the unit. These rules are collectively expressed on “What”. When constructing a task, at least one “What” needs to be included. “Who” represents the task assignment object and performer, and “Where” and “When” represent the space and time constraints of the task.

Thomas Remmersmann et al. [17] designed a control system for real robots to execute C-BML commands in 2010, and proposed a decomposition and planning system for C-BML tasks. Langerwisch et al. [18] developed a C-BML command-based control system for UAV and UGV with the Robot Operating System (ROS). In a heterogeneous cluster, UAV and UGV share information through C-BML and completed the corresponding tasks. The architecture of their system basically similar to Thomas Remmersmann, they combine ROS and C-BML using the BML Connector based on ROS, when distributing C-BML instructions from a high-level system. Schade et al. [19] have further discussed the grammar of C-BML. They believe that C-BML grammar should be: (1) context-free; (2) its vocabulary terms should be taken from Joint Consultation, Command and Control Information Exchange Data Model (JC3IEDM) [19]; (3) its non-terminal symbols should represent semantic roles; (4) it should be possible to repair the order of the components, making the clause semantically disambiguating.

B. NESTED VEHICLE ROUTING

In the cooperative setting, the UGV can serve as mobile base stations for the UAV, which will expand the effective flying distance for the UAV, and greatly improve mission efficiency. At present, there have been some related researches on cooperative vehicle routing. The earliest introduction by Murray and Chu [10] established a MILP model for the FSTSP. Since then, many variants with different objectives of this problem have been proposed: (1) Minimize the total delivery time [10], [20]-[22], and (2) Minimize the costs [23], [24]. In terms of the solution methods for FSTSP, some simple heuristic algorithms are designed based on the idea of saving swap and neighborhood search. In order to better solve this problem, people began to design improvement and perturbation operators with problem characteristics for such a UGV-UAV system, forming some algorithms with faster solution efficiency and better solution quality [25], [26].

Agatz [20] proposed the “Traveling Salesman Problem with Drone” (TSP-D) problem and the road network of drones and vehicles are the same, which is slightly different from FSTSP. This problem is also modelled as a mixed integer linear programming model, and a local search is used by the construction heuristic algorithm to improve the solution quality. Ha et al. [27] introduced the limitation of waiting time in this problem, that is, assuming that the drone and the vehicle will wait for each other within a long time limit. In terms of the solution methods for TSP-D, two heuristic algorithms, “UGV First UGV Second” and “UGV First UAV Second”, are designed. At present, scholars have further study the iterative algorithm with better solution quality [28], and give an accurate solution of a branch and bound based on theoretical analysis [29].

In addition, such nested vehicle routing planning (NVRP) problem has been expanded from the initial one-truck one-drone distribution [10], [20], [30]-[32] to the one-truck multi-drones delivery problem, the one-truck multi-drones delivery and pickup problem [33]-[36], and multiple trucks multiple drones problem [21], [22], [24], [35]. In recent years, several solution methodologies have been proposed to address the conundrum of nested vehicle routing through planning the paths of the UGV and UAVs to enable all customers to get packages, while ensuring that the time and energy consumed are minimized. A survey of UGV-UAV cooperation delivery [37] summarizes forty-eight paper, shows the percentage of common methods such as MILP, binary programming (BP), constraint programming (CP), dynamic programming (DP), non-linear programming (NLP), branch-and-bound algorithm (B&B), robust optimization (RO), quadratic programming (QP) and so on.
TABLE 1. The Classification of Publications Related to the Cooperate Between Truck (UGV) and Drone (UAV).

| Ref. | problem  | truck (UGV) number | drone (UAV) number | Solution |
|------|----------|-------------------|------------------|----------|
| [10] | FSTSP    | 1                 | 1                | MILP, heuristic approach |
| [32] | FSTSP    | 1                 | 1                | Heuristic |
| [28] | FSTSP, TSP-D | 1             | 1                | Dynamic programming and A* |
| [38] | TSP-D    | 1                 | 1                | GRASP, TSP-LS, MILP |
| [27] | TSP-D    | 1                 | m                | GA and K-means |
| [33] | TSP-D    | 1                 | m                | Theorems with worst-case scenarios |
| [39] | VRP-D    | n                 | m                | Theorems with worst-case scenarios |
| [40] | VRP-D    | n                 | m                | Joint path planning algorithm |
| [41] | VANDP    | 1                 | m                | Joint path planning algorithm |
| [42] | VANDP    | 1                 | m                | MILP |
| [43] | VANDP    | 1                 | m                | MILP |
| [44] | VRP-D    | 1                 | m                | MILP |
| [45] | TSP-D    | 1                 | m+n              | MILP |
| [46] | 2E-GUCRP | 1                 | 1                | MILP, Heuristic |
| [47] | 2E-GUCRP | 1                 | 1                | MILP, Heuristic |
| [48] | CAGVRP   | 1                 | 1                | MILP |
| [49] | CAGVRP   | 1                 | 1                | MILP |

We summarize the publications about NVRP and classify it by number of the vehicles in Table 1.

III. FORMULATION AND SOLUTION METHODOLOGY

A. FRAMEWORK OVERVIEW

Such as in the context of COVID-19, considering the controllability of contact among customers, we assumed that the UAV flight service only serves one customer every time. That is, in the delivery process, the UAV can take a package from the UGV, launch and deliver for the customer, and return to the UGV at one later customer point. The UGV and UAV move at the same time, but not independently. The movements of the UGV and UAV must be synchronized to allow the return of the UAV to UGV at discrete locations within endurable flight time. During the delivery of UAV, the UGV will wait for the return at the launch location, or a certain point for retrieve and launch again.

Commanding cooperative UGV-UAV for emergency resource delivery can be decomposed into some subtasks. As shown in Figure 2, the general overview of our proposed framework, after accepting the OPORD from the commander, the intelligent task understanding module of the UGV-UAV system will interpret the order. Basing on the knowledge base, the intelligent task understanding module and the scene and situation understanding module will cooperate to generate the planning problem and constraints for the vehicle planning system. The scene and situation understanding module is mainly based on scene graph generation technique with natural language-based semantic description [50]. We mainly focus on the design of the intelligent task understanding module and the nested vehicle routing planning module.

B. INTELLIGENT TASK UNDERSTANDING

Intelligent Task Understanding is a process that the commander’s instructions are resolved into 5w elements, and it is convenient for the unmanned system to understand task correctly and complete the command task.

To connect the graphical user interface (GUI) with the UGV and UAV, the BML is used in the BML Connector to connect the ROS system. As shown in the Figure 3, the...
operator communicates with the UGV with BML via the GUI, the UGV and UAV communicate through the ROS. All the BML formatted OPORD will be transmitted via the UGV. The GUI uses the Robot Command and Control Lexical Grammar (Robot-C2LG) to format the OPORD.

Interpreting the OPORD according to the C-BML grammar is analyzing tasks, areas, other locations, units, organization, reports information in the orders. The resulting 5W (what, where, when, who, why) elements will be padding for constructing the planning problem in the nested vehicle routing planning process.

OPORD includes task order, reporting order (location, capability, task status, and event report), request order. Such as one task is defined with the structure of the OPORD 5W elements, as shown in Figure 5.

The executor is specified in the TaskeeWho element. The one who is ordering is specified in the TaskerWho element. Where the action takes place is specified in the Where element. The start/end times are specified in the When element. The objects that are used or required during execution are specified in the Resource element. What to do is specified in the What element.

C. NESTED VEHICLE ROUTING PLANNING
The NVRP, similar to the FSTSP, is the problem of serving customers $C = \{1, \ldots, c\}$ with either a UGV or a UAV. We use the idea of “UGV First, UAV Second” to plan the nested vehicle routing, in which the UGV dominant the route, the UAV sortie should meet the UGV route.

1) PROBLEM MODELLING
The problem is built on digraph $G = (N, A)$, where the set $N = \{0, 1, \ldots, c + 1\}$ represents all the nodes, while we define $N_0 = \{0, 1, \ldots, c\}$ and $N_+ = \{1, \ldots, c + 1\}$. Let $A$ be the set of all the arcs $(i, j), i \in N_0, j \in N_+, i \neq j$. Each arc $(i, j)$ is associated with two non-negative traveling times: $\tau^G_{ij}$ and $\tau^A_{ij}$, which represents the time for traveling that arc by the UGV and by the UAV, respectively.

The travel time matrices of the UAV and the UGV are normally different. Nodes 0 and $c + 1$ represent the same

![Figure 4](image-url)

**FIGURE 4.** The intelligent task understanding module for the cooperative UGV-UAV system.

![Figure 5](image-url)

**FIGURE 5.** The intelligent task understanding module for the 5W elements for the C-BML format order.
physical point, the depot, and the traveling time between them is set to 0. One UGV is equipped with one UAV that can be used to serve one customer every time. The UGV starts from the depot and returns to the final depot $c + 1$. The UAV route is called sortie with a launching node, a served customer, and a retrieve node. All customers of $C$ can be served by the UGV, but only a subset $C' \subseteq C$ can be served by the UAV with a sortie.

a: UAV MODELLING

We use a triple $(i, j, k)$ to represent a sortie which has a launch node $(i \in N_0)$, a customer node $(j \in C')$, and a retrieve node $(k \in N_+)$ The power consumption of different flight phases is shown in Figure 6.

Each sortie can be divided into eight phases, as described in Table 2.

### TABLE 2. Speeds and Flight Times of Different UAV Flight Phases.

| Flight Phase                      | UAV Speed [m/s] | UAV Time [s] |
|-----------------------------------|-----------------|--------------|
| Launch from node $i$              | $\nu_i^l$       | $\tau_i^l = \frac{h_i}{\nu_i^l}$ |
| Horizontal cruise from $i$ to $j$ | $\nu_{ij}^c$    | $\tau_{ij}^c = d_{ij}/\nu_{ij}^c$ |
| Retrieve at node $j$              | $\nu_j^r$       | $\tau_j^r = \frac{h_j}{\nu_j^r}$ |
| Customer service at node $j$      |                 | $\sigma_j^c$ |
| Launch from node $j$              | $\nu_j^l$       | $\tau_j^l = \frac{h_j}{\nu_j^l}$ |
| Horizontal cruise from $j$ to $k$ | $\nu_{jk}^c$    | $\tau_{jk}^c = d_{jk}/\nu_{jk}^c$ |
| Wait for retrieval at node $k$    |                 | $\tau_k^w$ |
| Retrieve at node $j$              | $\nu_j^r$       | $\tau_j^r = \frac{h_j}{\nu_j^r}$ |

However, cruise speeds $\nu_{ij}^c$ and $\nu_{jk}^c$ are considered as decision variables. The minimum time required for the $(i, j, k)$, $(i \neq j \neq k)$ sortie is given by:

$$T_{ijk}^{\min} = \tau_i^l + \tau_{ij}^c + \tau_j^c + \sigma_j^c + \tau_j^r + \tau_k^w$$

(1)

$T_{ijk}^{\min}$ does not include the waiting time($\tau_k^w$) of UAV at the retrieval node. When completing a sortie, the maximum time of UAV operating is endurance, which depends on the power consumption of UAV. There are different power consumption in different flight phases, Since it is a function of speeds and payload weight. For example, the power consumption during vertical launch or retrieve phases is defined as $P^{\text{pl}}(w, v_c)$, as a function of parcel weight $w$ and speed $v_c$. The power consumption during cruising is defined as $P^{\text{c}}(w, v_{ho})$. The parcel weight is defined by power consumption of hover alone as $P^{\text{ho}}(w)$. The minimum energy required to maintain UAV for the duration of the $T_{ijk}^{\min}$ time unit is determined by Formula 2.

$$E_{ijk}^{\min} = \tau_i^l P^{\text{pl}}(w_j, v_j^l) + \tau_{ij}^c P^{\text{c}}(w_j, v_j^c) + \tau_j^r P^{\text{pl}}(w_j, v_j^r) + \tau_j^c P^{\text{pl}}(w_j, v_j^c) + \tau_j^w P^{\text{pl}}(w_j, v_j^w) + \tau_k^w P^{\text{pl}}(w_j, v_j^w)$$

(2)

The battery capacity is defined as $E^{\text{avail}}$, considering whether the minimum energy of a UAV sortie meets the battery capacity and has remaining energy for waiting time. Therefore, the waiting time is defined as $\tau_k^w$ and constrained by constrain 3, and the effective energy is defined as $e_{ijk}$ calculated by formula 4.

$$\tau_k^w \leq \frac{E^{\text{avail}} - E_{ijk}^{\min}}{P^{\text{pl}}(0)}$$

(3)

$$e_{ijk} = \begin{cases} 
T_{ijk}^{\min} + \frac{E^{\text{avail}} - E_{ijk}^{\min}}{P^{\text{pl}}(0)}, & \text{if } E_{ijk}^{\min} \leq E^{\text{avail}} \\
0, & \text{otherwise}
\end{cases}$$

(4)

We define the vertical speed of UAV as $v_v$ and the horizontal speed as $v_{ho}$, then the power consumption is calculated by formal 5-7. Where, the Equation 5 represents the power consumption of launch or retrieve with the vertical speed, the Equation 6 represents the power consumption of horizontal cruise with the horizontal speed, and the Equation 7 represents the power consumption of hover.

$$P^{\text{pl}}(w, v_c) = k_1(W + w)g \left[ \frac{v_c}{2} + \sqrt{\left(\frac{v_c}{2}\right)^2 + \frac{(W + w)g}{k_2^2}} \right] + c_2((W + w)g)^{3/2}$$

(5)

$$P^{\text{c}}(w, v_{ho}) = (c_1 + c_2) \left[ (W + w)g - c_5(\theta_{ho} \cos \alpha)^2 \right] + c_4 v_{ho}^{3/2}$$

(6)

$$P^{\text{ho}}(w) = (c_1 + c_2) ((W + w)g)^{3/2}$$

(7)

where, $c_1$, $c_2$, $c_4$, $c_5$, $k_1$ and $k_2$ are given in the model of paper [51] and shown in Table 3.

### TABLE 3. Values of Model Coefficient.

| Coefficient | $k_1$ | $k_2$ | $c_1$ | $c_2$ | $c_3$ | $c_4$ | $c_5$ |
|-------------|-------|-------|-------|-------|-------|-------|-------|
| Units       | [unitless] | [m/kg] | [m/kg] | [m/kg] | [m/kg] | [m/kg] | [Ns/m] |
retracted when the UGV is in the depot, customers, or even in motion. At the same time, we consider that the UAV is the automated launch and recovery systems. Some decision variables are depicted in Table 4.

### Table 4. Decision Variables.

| Mathematical Symbol | Description |
|---------------------|-------------|
| \( C \) = \{1,...,c \} | Set of all customers |
| \( N_0 \) = \{0,1,...,c+1\} | Set of all nodes |
| \( N_c \) = \{1,2,...,c+1\} | Set of nodes which UGV might depart |
| \( A \) | Set of all arcs (i,j), \( i \in N_0, j \in N_c, i \neq j \) |
| \( t_0 \) | Traveling time of UAV |
| \( t_0' \) | Traveling time of UGV |
| \( w_0 \) | Preparing launching time for UAV |
| \( \delta^0 \) | Retrieving time for UAV |
| \( E \) | Time of battery limit |
| \( x_{ij} \in \{0,1\} \) | Time of delivery order \( i \) to \( j \) |
| \( w_i \in \mathbb{R}^+ \), \( t_0 = 0 \) | Waiting time for UGV in the node \( i \) |
| \( \gamma_{ij} \in \{0,1\} \) | Completing time in the node \( i \) |

When UA V flies from the node \( i \) to node \( j \), then \( \gamma_{ij} = 1 \). The variable \( \gamma_{ij} \) is defined as \( (i,j) \in A \) and also defined as a feasible flying order of UAV as variable 1. \( \gamma_{ij} = 0, (i,j) \in A, \gamma_{jk} \neq 1 \) are the constraints used to define variable \( \gamma_{ij} \).

The objective function can be formulated as (9):

\[
\min \sum_{(i,j) \in A} t_{ij} G x_{ij} + \sigma L \sum_{(i,j) \in A} \gamma_{ij} + \sigma R \sum_{(j,k) \in A} \gamma_{jk} + \sum_{i \in N_+} w_i (9)
\]

Some constraints are as follows:

\[
\sum_{j \in N_+} x_{ij} = \sum_{i \in N_0} x_{i,c+1} = 1 (10)
\]

\[
\sum_{i \in N_0} x_{ij} = \sum_{i \in N_0} x_{ji} \quad j \in C (11)
\]

\[
\sum_{i \in N_0} x_{ij} + \sum_{i \in N_0} \gamma_{ij} = 1 \quad j \in C (12)
\]

\[
\sum_{i \in N_0} x_{ji} + \sum_{i \in N_0} \gamma_{ji} = 1 \quad j \in C (13)
\]

\[
t_j \geq t_i + t_{ij} - \tau_{ij}^G - M (1 - x_{ij}) \quad (i,j) \in A (14)
\]

\[
t_j \geq t_i + \tau_{ij}^A - M (1 - \gamma_{ij}) \quad (i,j) \in A (15)
\]

\[
t_k \geq t_j + \tau_{jk}^A - M (1 - \gamma_{jk}) \quad (j,k) \in A (16)
\]

\[
t_k - t_l + \sigma_R - M (2 - \gamma_{lj} - \gamma_{jk}) \leq E \quad i \in N_0, j \in C', k \in N_+ (17)
\]

\[
\sum_{i \in N_0, j \in C'} \gamma_{ij} - \sum_{k \in N_+} \gamma_{jk} \quad j \in C' (18)
\]

\[
\sum_{i \in N_0} x_{ij} + \sum_{i \in N_0} \gamma_{ij} \leq |P| (19)
\]

\[
\sum_{i \in N_0} \gamma_{ij} + \sum_{i \in N_0} \gamma_{ji} \leq 1 \quad (i,j) \in A (20)
\]

\[
\gamma_{ij} + \gamma_{ji} \leq 1 \quad (i,j) \in A (21)
\]

Constraint (10) constrains the depot to be the start and final node in UAV route. Constraint (11) constrains flow balance for UGV. Constraint (12) and (13) are the customers covering constraints, which impose that all customers need be served either by UGV or UAV. Constraint (14) is used for timing constraints, that the time in node \( j \) is at least travelling time from node \( i \) to node \( j \) plus the time in node \( i \). Constraint (15) constrains the waiting time for UGV, if the UAV arrivals at retrieve node earlier than the UGV, it must be waiting for UGV, and the waiting time is the difference of UGV’s and UAV’s arrival times. However, if the UAV arrivals at retrieve node earlier than the UGV, it must be waiting for UGV when it flying. So, the waiting time is included in travelling time of UGV (constraint (14)). Constraint (16) and (17) represent the times updating of launch process and retrieve process of UAV. Constraint (19) constrains UAV’s total time by limitation of battery capacity. Constraint (20) constraints fling rules of UAV, which the UAV must return to UGV after serving customer. Constraint (21) and (22) are the x-y coupling constraints, they constrain the process of UAV launch and retrieve must be in a node which both the UAV and UGV are located in that node. Constraint (24) can avoid UAV crossing sorties. When node \( i \in N_0 \) and node \( l \in N_+ \) are start and final node of UAV route \( P = \{v(1), v(2), \ldots, v(q)\} \), where \( v(1) = i, v(q) = l \), we use the following constraint to ensure that there is no crossing part between two UAV routes \( \gamma_{ij} > 0, \gamma_{lm} > 0 \). It just avoid the two case in Figure 7. Constraint (25) and (26) can avoid UAV route infeasibility.

### 2. DELIVERY MODELLING

Our formulation is based on the model presented in [52]. We use only one set of time variables to define the time of UGV and UAV synchronization so that we can have its number and use fewer “big-M” constraints, where the M is one big enough positive value.

In our model, we use two-indexed binary variables represent the launch and retrieve process. When the UAV launches at node \( i \in N_0 \), flies from node \( i \) to node \( j \), and serves the customer at node \( j \in C' \), the variable defines \( \gamma_{ij} = 1 \). And when UGV flies from the node \( j \) to node \( k \in N_+ \), and retrieves at node \( k \), the variable defines \( \gamma_{jk} = 1 \). To reduce the number of variables, the variables which do not meet the battle capacity, will be defined as 0. \( (\gamma_{ij} = 0, \gamma_{ij} \neq 0, \gamma_{jk} = 0, \gamma_{jk} = 1) \)

And we also define a feasible flying order of UAV as variable 0. \( (\gamma_{ij} = 0, \gamma_{ij} = 1, \gamma_{jk} = 0, \gamma_{jk} = 1) \)

In this section, we first consider the route of the UGV and then the sortie of the UAV base on the idea of “UGV First UAV Second”, we design one three-stage solution.
approach. In the first stage, we use the Lin-Kernighan heuristic (LKH) algorithm [53] to generate the TSP solution for the UGV. In the second stage, we use the Clarke and Wright (CW) [54] saving heuristic algorithm to generate the baseline solution for the UGV-UAV, in which

\[
T_o - T_n = D_a - 2C_{a,b} + D_b
\]

where \(C_{a,b}\) is the cost of edge between node \(a\) and node \(b\).

The purpose of this algorithm is to find the best sequence of interchange operations between the elements in \(A\) and \(B\), so as to maximize \(T_o - T_n\), and then perform these operations. Thus, the graph is divided into \(A\) and \(B\).

In this algorithm, the UGV starts from the depot and delivers to the unvisited node which has the minimum penalty and cost, each time until all target points are visited. The algorithm runs fast and can quickly construct UGV routes, but the quality of the final solution largely depends on the layout of the target node.

\textbf{Algorithm 1 Lin-Kernighan Heuristic Algorithm}

\textbf{Input:} graph \(G = (V, E)\)

\textbf{Output:} balance initial partition of the nodes into sets \(A\) and \(B\)

Compute \(D\) values for all \(a\) in \(A\) and \(b\) in \(B\)

Let \(gv, av,\) and \(bv\) be empty lists

FOR \(n := 1\) to \(|V| / 2\) DO

find \(a \in A\) and \(b \in B\), such that \(g = D[f[a]] + D[b] - 2 \times C(a, b)\) is maximal

remove \(a\) and \(b\) from further consideration in this pass

add \(g\) to \(gv\), \(a\) to \(av\), and \(b\) to \(bv\)

update \(D\) values for the elements of \(A = A \setminus a\) and \(B = B \setminus b\)

END \(g_{\text{max}} > 0\)

Find \(k\) which maximizes \(g_{\text{max}}\), the sum of \(gv[1], \ldots, gv[k]\)

WHILE \(g_{\text{max}} > 0\)

Exchange \(av[1], av[2], \ldots, av[k]\) with \(bv[1], bv[2], \ldots, bv[k]\)

END WHILE return \(G(V, E)\)

The input of algorithm is a graph \((G = (V, E))\), where the \(V\) represents the set of vertex, and the \(E\) represents the set of edge and each edge has a weight. The purpose of algorithm is to divide \(V\) into two equal and disjoint subsets \(A\) and \(B\) to minimizes the sum \(T\) of the weights of the subset of edges that cross from \(A\) to \(B\). If the graph is not weighted, we divide a weight into the subset edge to minimize the crossing edges number. The algorithm uses a greedy algorithm to update the partition, matches \(A\) and \(B\) vertices, and move pairs of vertices from one side to the other to improve the partition. After the vertices are paired up, the subset with the best overall effect is selected. The time complexity of the algorithm with \(n\) nodes is \(O(n^2 \log n)\). We define the sum of internal cost between node \(a\) \((a \in A)\) and other nodes in subset \(A\) as \(I_a\) and define the sum of external cost between the nodes \(a\) and all nodes in subset \(B\) as \(E_b\). Similarly, we get \(I_b, E_b\) when node \(b\) is in subset \(B\) \((b \in B)\). The difference between external and internal costs of node \(a\) is \(D_a = E_a - I_a\).

\[
D_a = C_{a-b}^G + C_{b-c}^G
\]
Equivalently, the transportation cost $D_b$ in Figure 8 (b) is:

$$D_b = C_{a-c}^G + C_{a-b}^A + C_{b-c}^A$$  (29)

In this way, the cost of UGV-UAV route obtained by the saving algorithm is:

$$S = D_a - D_b = C_{a-c}^G + C_{b-c}^G - (C_{a-c}^G + C_{a-b}^A + C_{b-c}^A)$$  (30)

After LKH heuristic algorithm, we get a directed UGV route that includes all target nodes. However, it is obvious that part of the target points can be delivered by the UAV. And then, it can greatly reduce the driving distance or cost of the UGV. Therefore, we propose a strategy of maximum cost-saving based on the saving algorithm proposed by Clarke and Wright, which tries to minimize the cost by changing the target point of UGV delivery to UAV delivery. The CW saving algorithm was originally applied to the vehicle routing problem (VRP). Its purpose is to find the optimal path for all given target points. The main idea is to find the maximum distance reduction by combining two routes into one route under the limitation of UGV load. The algorithm discusses and calculates each target point currently located on the UGV route in each round of the cycle, and then transfers the target point with the most cost savings after changing the method to UAV for delivery.

![Figure 9. Schematic solution of 7 target point cases by heuristic algorithm.](image)

As shown in Figure 9, the circle point is represented the custom point, the rectangles point is represented the depot. We propose a hybrid heuristic based on LKH and CW shown in Algorithm 2, and first use the LKH algorithm to construct a directed main route for UGV to visit all target nodes (as shown in Figure 9(a)). Then, using the idea of maximum cost savings, some UGV nodes are replaced with UAV nodes to obtain the UAV companion route (shown in Figure 9 (b)).

According to the CW saving algorithm, check all the target nodes on the main route of UGV, calculate the cost saved by each replaceable node, and after all calculations are completed, the node with the most cost saving will be delivered by UAV. Repeat this calculation and replacement steps until there are no replaceable UGV nodes or the replacement still cannot save costs, which means that the total cost can no longer be reduced by changing the target delivery method.

### Algorithm 2: The CW Saving Heuristic Algorithm

**Input:** UGV route  
**Output:** UGV-UAV route  

**COMPUTE** maximum UGV route

**WHILE** (1)

1. **Find MostSavingTargetPoint**
2. **IF** MostSavingTargetPoint
   - turn UGV delivery point B into UAV delivery point
3. **ELSE**
   - break
4. **END IF**
**END WHILE**

**return** UGV-UAV routes

#### 3) ITERATIVE IMPROVEMENT

In the previous section, we adopted the LKH and CW saving algorithms to solve the NVRP, however, the feasible solutions constructed still need optimization and adjustment. Therefore, we propose a learning based iterative improvement algorithm for solving NVRP. As shown in Algorithm 3, we design six different improvement operators.

### Algorithm 3: Learning Based Iterative Improvement Algorithm

**Input:** An initial tour $\tilde{R}$; a partitioning algorithm $f$; a neighborhood function $N$

**Output:** A locally optimal tour for a neighborhood function $\tilde{R}$

**$\tilde{R}$** ← $R$

$i$ ← True

**WHILE** $i$ DO

1. $i$ ← False
2. $M$ ← $N(R)$
3. **FOR** $m \in M$ **DO**
4. **Modify** $R$ according to move $m$
5. **IF** $f(R) < f(\tilde{R})$ **THEN**
6. $\tilde{R}$ ← $R$
7. $i$ ← True
8. **END IF**
9. **END**
10. **Modify** $R$ by the inverse of move $m$
11. **END**
12. **END**
13. **RETURN** $\tilde{R}$

**a: INTRA-ROUTE SWAP**

This operator achieves to swap a target point with another one which both of them are in the same route, when the swap cannot result in an infeasible route because of the endurance constraint and the launch and retrieve sorties of UAV. Due to the flight constraint of UAV, the route can be swapped only be implemented on UGV route. We swap the target point $b$ and $f$ by this operator as shown intuitively in Figure 10.

b: INTER-ROUTE SWAP
This operator achieves to swap a target point with another one that they are in the different routes when the swap cannot result in an infeasible route because of the endurance constraint and the launch and retrieve sorties of UAV. We swap the target point b in the UGV route and c in the UAV route by this operator as shown intuitively in Figure 11.

c: INTER-ROUTE SHIFT
This operator achieves to relocate a target point in the intra route when the relocation cannot result in an infeasible route because of the endurance constraint and the launch and retrieve sorties of UAV. Due to the flight constraint of UAV, the route can be swapped only be implemented on UGV route. We relocate the target point b in the UGV route and the new location of target point relocated divided into two different situations as shown intuitively in Figure 12.

d: GROUP INTER-ROUTE SWAP
This operator achieves to swap a target point group with another group which both of them are in the same route, when the swap cannot result in an infeasible route because of the endurance constraint and the launch and retrieve sorties of UAV. Due to the flight constraint of UAV, the route can be swapped only be implemented on UGV route. Taking the group swapped both two target points, we swap the target point group (b,c) in the UGV route and group swapped divided into two different situations as shown intuitively in Figure 13.

e: GROUP INTRA-ROUTE SHIFT
This operator achieves to relocate a target point group in the intra route when the relocation cannot result in an infeasible route because of the endurance constraint and the launch and retrieve sorties of UAV. Due to the flight constraint of UAV, the route can be swapped only be implemented on UGV route. Taking the group relocated two target points, we relocate the target point group (b,c) in the UGV route and the new location of target point relocated divided into two different situations as shown intuitively in Figure 14.

f: INVERSE ROUTE
This operator achieves to inverse partial UGV route. Considering whether the inverse partial UGV route include the UAV launch and retrieve target point, we divided it into two different situations as shown intuitively in Figure 15.
IV. EXPERIMENT

In this section, we design some experiments based on emergency resource delivery cases and the three-stage approach is tested based on some randomly generated instances.

A. EXPERIMENT SETUP

1) PROBLEM DEVELOPMENT

To explore the performance of the iterative improvement algorithm, we generate 60 problem instances with varying number of customers to conduct the experiment. 20 instances for three different scale (10, 50, 100) are generated. For each scale of customers, 10 instances with the depot center located, 10 instances with periphery located. The coordinates of the customer points are obtained from the Google map with the format latitude and longitude. The UGV travel times were generated via a PostgreSQL extension called pgRouting [55]. The UAV we choose is the DJI Phantom 4 Pro [56], with the travel times calculated with Euclidean distance.

2) UGV-UGV SPECIFICATION

The parameters value of the UGV and UAV are set according to practical cases. As described by [51], the non-linear model with power consumption can be employed to model the UAV endurance.

For simplification, the UAV is set to carry a maximum payload parcel of 3 kg and maximum distance of 10 kilometers. The UGV can finish a delivery task without refuelling. All the parameters are reported in Table 5, where the values of coefficient are correspond to the Table 2.

| UGV | speed | 50km/h |
|-----|-------|--------|
| UAV | payload | 3kg |
|     | battery capacity | 5870mAh |
|     | coefficient | 0.8554/0.3051/2.8037/0.3177/0.0296/0.0279 [51] |

B. EXPERIMENTAL RESULTS

The results of the initial solution obtained by the LKH and CW Saving Based Heuristic (LCH) and final solution by saving based iterative improvement (SII) for every instance are included for statistics. All the computational results for 60 instances in three scales are presented in Table 6. We run each algorithm for 20 times and display the average results. More detail are shown in Table 7.

| Scale | Nodes | LCH (hh:mm:ss) | SII(hh:mm:ss) | Gap(%) |
|-------|-------|----------------|---------------|--------|
| Small | 10    | 00:58:58       | 00:49:20      | 16.3   |
| Medium| 50    | 03:52:21       | 03:18:54      | 14.4   |
| Large | 100   | 05:27:32       | 04:53:15      | 10.4   |

As illustrated above, the SII algorithm significantly improve the initial solutions obtained by the LCH algorithm. For small-scale instances, the gap ratio between the saving based iterative improvement solution methodology (SII) and the initial solutions (LCH) is 16.3%. The object of the initial solution obtained by LCH for other two scales of instances are also reduced by 14.4% for medium ones and 10.4% for large ones. It can be proved that the iterative improvement does be effective.

V. CONCLUSION

In this article, we present the approach of command- ing cooperative UGV and UAV for emergency resource delivery. Experimental results indicate that the employment of UGV-UAV for delivery is applicable. The C-BML based OPORD understanding proves to be applicable in human-robot interaction. Randomly generated problems with different scales and case study show the efficiency of the
TABLE 7. Experimental Results.

| Instance | Opt(s) | Time(s) | Instance | Opt(s) | Time(s) | Instance | Opt(s) | Time(s) |
|----------|--------|---------|----------|--------|---------|----------|--------|---------|
| 1-10     | 4154.85| 0.13    | 50-1     | 12044.17| 7.85    | 100-1    | 11925.09| 82.78   |
| 1-2      | 4563.05| 0.03    | 50-2     | 13199.90| 6.89    | 100-2    | 11944.83| 68.16   |
| 1-3      | 4305.37| 0.06    | 50-3     | 12933.52| 6.78    | 100-3    | 20020.26| 79.10   |
| 1-4      | 5047.77| 0.07    | 50-4     | 13669.25| 7.65    | 100-4    | 18991.33| 84.53   |
| 1-5      | 4249.11| 0.06    | 50-5     | 12978.07| 7.04    | 100-5    | 19298.62| 78.06   |
| 1-6      | 5470.70| 0.04    | 50-6     | 13137.52| 7.73    | 100-6    | 18222.37| 57.88   |
| 1-7      | 4231.84| 0.04    | 50-7     | 12622.43| 10.40   | 100-7    | 19546.59| 93.24   |
| 1-8      | 5704.49| 0.07    | 50-8     | 9415.11 | 10.06   | 100-8    | 14582.06| 165.50  |
| 1-9      | 5068.51| 0.04    | 50-9     | 9115.80 | 10.71   | 100-9    | 14097.70| 131.73  |
| 1-10     | 4453.37| 0.04    | 50-10    | 9460.17 | 8.12    | 100-10   | 14605.15| 136.54  |
| 1-11     | 1236.29| 0.08    | 50-11    | 8700.15 | 7.82    | 100-11   | 14948.20| 139.56  |
| 1-12     | 1390.44| 0.13    | 50-12    | 8769.69 | 6.66    | 100-12   | 14490.86| 135.90  |
| 1-13     | 1510.36| 0.09    | 50-13    | 9333.15 | 6.52    | 100-13   | 14234.09| 151.50  |
| 1-14     | 1174.88| 0.09    | 50-14    | 8493.10 | 12.11   | 100-14   | 18954.95| 71.00   |
| 1-15     | 1473.45| 0.06    | 50-15    | 9610.33 | 13.54   | 100-15   | 14562.51| 129.18  |
| 1-16     | 1649.19| 0.06    | 50-16    | 12538.52| 6.05    | 100-16   | 14424.83| 134.22  |
| 1-17     | 1352.25| 0.10    | 50-17    | 13216.66| 3.82    | 100-17   | 18485.36| 73.07   |
| 1-18     | 1504.47| 0.06    | 50-18    | 11522.21| 5.65    | 100-18   | 14797.81| 156.09  |
| 1-19     | 1611.50| 0.07    | 50-19    | 8563.20 | 9.34    | 100-19   | 18287.86| 78.73   |
| 1-20     | 1206.84| 0.09    | 50-20    | 9120.98 | 11.49   | 100-20   | 14176.10| 142.16  |

Appendix. Experimental Results

See Table 7.

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