A Research on Vehicle and UAV Routing Problem during Distribution Based on IAMMAS

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Abstract. According to the characteristic of vehicle and unmanned aerial vehicle (UAV) in distribution service, a vehicle and UAV distribution mode were put forward in this paper to further expand the three-dimensional space of distribution, improve the efficiency of distribution and relieve the pressure of distribution personnel. Based on the consideration of real-time road condition, real-time driving speed, maximum driving distance and mixing time windows in distribution practice, a two-stage nested VRPTW model under vehicle and UAV distribution mode was constructed in this paper. A hybrid algorithm of genetic algorithm and adaptive max-min ant system algorithm (GA-AMMAS) was designed to solve the above problems. In addition, the actual road traffic conditions and vehicle actual travel time were added to the heuristic information in this algorithm. Data experiments shows that the vehicle and UAV routing problem can be effectively solved by GA-AMMAS. In addition, compared with GA and ACA, GA-AMMAS shows obvious advantages in quality solution and speed of convergence.

1. Introduction
In recent years, unmanned aerial vehicle (UAV) distribution model has made great progress. It can be traced back to the war in Afghanistan when the U.S. military unmanned transport aircraft K-MAX has successfully completed the equipment support tasks of weapons, ammunition, materials and oils from the logistics base to the front positions in remote mountainous areas, marking that UAV formally marched into the field of wartime distribution as an air porter. With the rapid development of artificial intelligence, UAV distribution technology is becoming popular at home and abroad, and its commercial distribution is gradually legalized. In August 2017, the door-to-door UAV delivery service was implemented in Reykjavik; in October of the same year, UAV was used to deliver blood to clinics in Rwanda at speeds of up to 100 km/h by ZIPLINE; in addition, a large number of UAV delivery experiments has been worked by Amazon. In China, in July 2017, a large logistics UAV headquarters base was established by SF-express, and a concept of a three-stage air transport network of large-scale UAV 10-terminal small UAV with 10 branches of large-scale manned transport aircraft to achieve 36 hours access to the whole country and cover all terrain complex areas and remote areas was proposed. In the same year, a six-rotor UAV with a flying radius of 20km and a sailing speed of 54 km / h was developed by JD. In 2018, UAV take-out and express delivery routes were allowed to be opened, which realized the legalization of UAV take-out and distribution, greatly improved the efficiency of distribution, and created great convenience for the public.

However, the current UAV is limited by its small load and limited flight radius, which makes it difficult to achieve the distribution task alone in most cases. In view of this, a vehicle and UAV distribution mode which can be applied to the restricted distribution areas such as high-rise buildings,
remote mountainous areas and plateau mountainous areas was proposed in this paper, in order to realize the 3D space expansion of distribution areas, improve distribution efficiency and relieve the pressure of distribution personnel by complementing the advantages of vehicles and UAV.

The essence of vehicle routing optimization, UAV routing optimization and vehicle and UAV routing optimization belongs to the category of vehicle routing problem (VRP). This problem was first raised by Dantzing in 1959. It is a typical NP-hard problem. Vehicle routing problem with time windows (VRPTW), a variant of VRP, is a hot and difficult problem in the field of logistics. The improvement of model and solution has been widely studied by a wide range of scholars mainly to solve the problem above. For example, a series of VRPTW models such as urban distribution, Internet car rental and dangerous goods transportation under congestion were constructed [1,2], and a lot of VRPTW solving algorithms such as improved ant colony algorithm, improved genetic algorithm and bat algorithm was designed [3,4]. On the basis of previous research [5], a VPRTW model of vehicle and UAV is constructed in this paper. In addition, according to the characteristics of the problem, an improved adaptive max-min ant colony algorithm (IAMMAS) is applied to solve the problem.

2. A vehicle and UAV distribution model

2.1. Vehicle distribution model
Vehicle distribution refers to the organization of appropriate driving routes for a series of unloading (loading) points, and the orderly passage of vehicles through them under certain constraints (such as cargo demand, delivery volume, delivery time window, vehicle capacity limitation, time limitation, etc.) in order to achieve certain goals (such as the shortest distance, the lowest cost, the shortest time, etc.). Its characteristics are economy of scale, but its unit distribution cost is high, its cargo load is large, its driving range is wide, but it is greatly affected by the terrain [6].

2.2. UAV distribution model
Unmanned Aerial Vehicle (UAV) is a kind of unmanned aerial vehicle. It uses internal radio remote control equipment and pre-programmed control program to realize autonomous flight and independently complete combat or support tasks. It is flexible, concealed and efficient, safe and economical, less affected by weather, terrain, road traffic, and three-dimensional distribution space (see Figure. 1), but it has limited load and smaller flight radius. At present, China's UAV has more mature distribution performance, such as six-rotor UAV, which has the characteristics of stability, flexibility, low cost, waterproof, high hanging, less affected by weather (e.g. Category 6 gale, typhoon, and rainy day), and adaptability to complex terrain (e.g. plateau mountain) [7,8].

![Figure 1 Diagram of UAV distribution path in 3D Space](image)

2.3. A vehicle and UAV distribution model
At present, the user needs of express delivery and meal delivery industries are distributed in communities, with small demand, strong timeliness and mostly located in areas with limited vehicle capacity (such as high buildings, residential streets and even remote mountainous areas). The traditional vehicle and manpower and vehicle and motorcycle model distribution efficiency is not high, and the work pressure of distribution personnel is heavy. Through the analysis of the complementary
advantages of UAV and vehicle (see Table 1), this paper proposes a vehicle and UAV distribution mode [9].

| Mode | Load | Speed | Cost | Range Restriction | Customer |
|------|------|-------|------|-------------------|----------|
| Vehicle | Big | Middle | Big | Much | Intensive |
| UAV    | Small | High   | Small | Small | Little    | Dispersed |

The specific distribution process of this model is as follows: the information department pre-processes the acquired user needs through cluster analysis, clustering the nodes located in the inaccessible areas of vehicles into demand communities. According to the requirement nodes of good traffic area, vehicles are distributed by vehicles, and UAV distribution principle is used in restricted traffic area. Through the study of the relevant literature, the movement forms of vehicle and UAV distribution mode is summarized into three types in this paper: (a) when the traffic conditions of vehicles are good, UAV will not be used temporarily; (b) vehicles are restricted by the scope of traffic, vehicles wait at a certain distribution point, and UAV is enabled for distribution, and after distribution, UAV returns to the vehicle; (c) Both are in motion. Due to state of (c) needs meet strict environmental and technical requirements, most of the cases are in the alternating state of (a), (b) two forms of movement.

3. Model design of vehicle and UAV distribution

3.1. Problem Description

The essence of vehicle and UAV routing problem is two-level nested VRPTW problem. Vehicle routing planning is a class \[ \text{VRPTW} \] problem and UAV distribution is a class \[ \text{VRPTW} \] problem. Construct level I undirected network \( G_{V} \), in which node set \( V \) includes warehouse, user and hubs of vehicle accessible area, and edge set \( E = \{arc(i, j) \mid i, j \in V_i \} \). Build level II undirected network \( G_{VII} \), and \( V \) includes users and hubs in restricted areas, and side collection is \( E_{VII} = \{arc(i, j) \mid i, j \in V_{VII} \} \). Since the start node needs to be returned after the task is completed, the endpoint is marked as the \( N+1 \) node in order to distinguish easily. \( arc(i, j) \) is the section of \( i \rightarrow j \) slave node, and its corresponding distance, speed, travel time and unit distance cost are \( s_{ij} \), \( v_{ij} \), \( t_{ij} \), \( c_{ij} \) respectively. In order to improve the reliability of the model, the distance correction factor \( h_{ij} \) and speed correction factor \( g_{ij} \) and the relationship between the vehicle load rate \( p_{ijk} \) and the unit cost of fuel/power consumption are introduced to correct the above \( s_{ij} \), \( v_{ij} \), \( t_{ij} \), \( c_{ij} \). The calculation of \( p_{ijk} \) is shown in formula (1), where \( y_{ij}^{k} \) is 0-1 variable, and if the node \( g \) is served by the transport vehicle \( k \), it is 1, otherwise it is 0. The revised variables are \( s_{ij} = h_{ij} \cdot d_{ij} \), \( v_{ij} = g_{ij} \cdot v_{ij} \), \( t_{ij} = s_{ij} / v_{ij} \), \( c_{ij} = \theta_{1} + p_{ijk} (\theta_{2} - \theta_{1}) \). Among them, \( d_{ij} \) is the straight line distance between \( i \) and \( j \), \( \bar{V}_{ij} \) is the average speed, and \( \theta_{1}, \theta_{2} \) is the unit distance cost of no-load and full-load. \( h_{ij} \geq 1 \), \( g_{ij} \leq 1 \) and \( h_{ij} \) are related to the degree of road bending fluctuation. The larger the \( h_{ij} \) of curved and steep sections, the greater the \( g_{ij} \) is related to road grade and road traffic condition. The higher the road grade and road traffic, the greater the \( g_{ij} \). \( h_{ij} \), \( g_{ij} \) can be assigned by the information platform according to the real-time road information acquired by \( arc(i, j) \). When it is not affected by the above factors, \( h_{ij}, g_{ij} \) takes 1. \( \theta_{1}, \theta_{2} \) is based on the historical data of vehicle fuel consumption. Warehouse 0 can be used as \( k \in \{1, 2, ..., K_{V} \} \) for the same type vehicle and \( k \in \{1, 2, ..., K_{U} \} \) for the same type UAV. The fixed cost of transport is \( c_{ijk} \), which is calculated according to the number of transport vehicles used. \( R_{k} \) is a variable of 0-1. If the vehicle is
used, take 1, otherwise take 0. The service time \( T_{\text{unload},ik} \) of a single user is related to the weight of the unloaded equipment and the average unloading speed \( \bar{v}_{\text{unload},ik} \), that is to say \( T_{\text{unload},ik} = q_i / \bar{v}_{\text{unload},ik} \).

\[
p_{ij,k} = \left( Q_k - \sum_{g \in \text{unload}} q_g \cdot y_g^k \right) / Q_k, \quad k = 1,2,\ldots,K
\]

Vehicles are orderly distributed from warehouse 0 to nodes in \( V_1 \). When it travels to the hubs of restricted area, UAV is used for service. When UAV distribution is enabled, UAV starts from the distribution point and returns to the vehicle at the distribution point after orderly service of the nodes. The vehicle then continues to visit the next user, hubs or return to the warehouse along the planned route. After completing the distribution task, the vehicle returns to warehouse 0 with UAV.

### 3.2. Model Hypothesis

1. Vehicles carrying cargo and UAV start from the warehouse and return to the warehouse after orderly visiting the nodes of \( V_1 \) in progress.

2. UAV starts from the hub and returns to the hub after orderly visiting the nodes of \( V_{\text{hl}} \) in progress.

3. A single vehicle corresponds to a path, and each user on each path only allows one vehicle to serve it, and can only access it once.

4. The total demand on each route shall not exceed the maximum load \( Q_k \), volume \( V_{\text{max}}^k \) and size of the vehicle.

5. Warehouse and each demand node have a time window \([ET_i, LT_i]\). If the time window exceeds, it will have to bear a certain penalty cost \( M(t_{ik}) \).

6. Transporters have a maximum driving distance limit (the maximum driving distance \( D_k \) is the ratio of current energy consumption \( E_k \) to energy consumption per unit distance \( e_k \), \( D_k = E_k / e_k \)).

### 3.3. Model Construction

\[
\min z = w_1 \cdot \sum_{i=1}^{N} \sum_{j=1}^{N} h_i \cdot d_{ij} \cdot x_{ij} - \frac{Q_k - \sum_{j=0}^{N} q_j \cdot x_j}{Q_k} \cdot \sum_{i=0}^{N} \sum_{j=1}^{N} h_i \cdot d_{ij} \cdot x_{ij} + w_2 \cdot \sum_{i=0}^{N} \sum_{j=1}^{N} \sum_{l=0}^{K} h_i \cdot d_{ij} \cdot x_{ij} - \sum_{i=0}^{N} \sum_{j=1}^{N} \sum_{l=0}^{K} M(t_{ij}) \cdot \delta_{ij} \\text{subject to:} \\
\sum_{j=1}^{N} q_j \cdot x_{ik} \leq Q_k, \quad \sum_{j=1}^{N} V_j \cdot x_{ik} \leq V_{\text{max}}^k, \quad b_j \leq \frac{V_j}{\sum_{j=1}^{N} V_j} V_{\text{max}}^k, \quad \forall k \in \{1,2,\ldots,K\} \\
\sum_{j=1}^{N} h_i \cdot d_{ij} \cdot x_{jk} \leq E_i / e_k, \quad i \neq j, \forall k \in \{1,2,\ldots,K\} \\
\sum_{i=0}^{N} \sum_{j=1}^{N} x_{ij} = 1, \quad \forall j \in \{1,2,\ldots,N+1\}, i \neq j \\
\sum_{j=1}^{N} x_{kj} \leq 1, \quad \forall k \in \{1,2,\ldots,K\} \\
\sum_{i=0}^{N} x_{ij} = \sum_{i=0}^{N} x_{ij}, \quad \forall j \in \{1,2,\ldots,N+1\}, \forall k \in \{0,1,\ldots,K\}, \quad i \neq j \\
\sum_{j \in S} \sum_{i \in S} x_{ij} \leq |S| - 1, \quad i \neq j, \forall S \subseteq \{1,2,\ldots,N\}, \forall k \in \{1,2,\ldots,K\} \\
x_{ij} = \begin{cases} 1, \text{Transport } k \text{ go from node } i \text{ to node } j \\ 0, \text{otherwise} \end{cases}
\]
waiting time of transport $k$ at node $i$ and $t_{i,k} = t_{w,k} + t_{w_{i,k}} + T_{t_{i,k}} + t_{j,k}$ is the time when transport $k$ arrives at node $j$. In order to improve the applicability of the model to multiple time windows, the penalty function $M(t)$ is used in this paper. $M(t)$ without time window requirement. Under the hard time window, $t_{i,k} \in [ET, LT], M(t) = 0; t_{i,k} \notin [ET, LT], M(t) \rightarrow \infty$. Under the soft time window and mixed time window, the specific expression of $M(t)$ is determined according to the user's requirements. Formula (3) denotes weight, volume and size constraints. $V_j$ is the volume of goods and $b_j$ is the size of goods. Formula (4) denotes the maximum distance of the transport $k$. Formula (5) denotes that there is only one vehicle at each point responsible for delivering the goods required. Formula (6) means that each vehicle is responsible for the distribution of up to one route, Formula (7) means the flow balance, Formula (8) means the constraints to prevent the occurrence of soliton rings. Formula (9) is 0-1 decision variable.

Two-stage method can be used to deal with this two-stage nested VRPTW problem. In the first stage, the hierarchical distribution network nodes are obtained on the basis of clustering analysis, and the path planning of UAV in the network is carried out. In the second stage, on the basis of the first stage, the demand information of all the demand nodes in the level distribution network is aggregated into their corresponding hubs, which are regarded as a virtual node in the level network (at this time, the demand of the hubs is the total demand of the customers in the corresponding level network plus the weight of UAV to perform tasks, and the lower limit of acceptable service time is the earliest available for the corresponding customers). The minimum value of receiving service time, the upper limit of acceptable service time is the maximum value of the corresponding customer's latest acceptable service time and the time when UAV completes the distribution task, and the service time is the total time when UAV performs the task. Then the vehicle routing in the level distribution network is planned according to VRPTW

4. Improved ant colony algorithm

4.1. Improvement Strategy

In this paper, an improved adaptive maximum and minimum ant colony algorithm (IAMMAS) is proposed to solve the above problems. When ant chooses the next node, not only capacity constraints, time window constraints and pheromone concentration and heuristic information concentration should be considered, but also road traffic, time window urgency and actual time consumed by the section does [10]. Therefore, in order to improve the reliability of ant search, this paper introduces path correction factor $h_j$ and speed correction factor $g_j$ in $n_j$. At the same time, $w_j(t)$ is introduced to eliminate the infeasible sections directly between nodes and reduce the search range of ants to improve ant search. Efficiency. The strategies for ants to choose the next node are as follows:

\[
\begin{align*}
  \left\{ \begin{array}{l}
    j = \arg \max \left[ \tau_y(t) \right] \left[ \eta_y(t) \right] \quad , q \leq q_0 \\
    P_y(t) = \frac{\left[ \tau_y(t) \right] \left[ \eta_y(t) \right] }{\sum_{s \in allowed} \left[ \tau_y(t) \right] \left[ \eta_y(t) \right]} , q > q_0 \\
    0, otherwise
  \end{array} \right.
\end{align*}
\]

\[
\begin{align*}
  \tau_y(t + \varepsilon) &= (1 - \rho) \tau_y(t) + \Delta \tau_y(t) \min \\
  \Delta \tau_y(t) &= \frac{O}{L}, L = \min(L_y) \\
  \Delta \tau_y(t) &= \frac{\sum_{i=1}^{n} \Delta \tau_i(t)}{\sum_{i=1}^{n} \Delta \tau_i(t)} \\
  \tau_y(t) &\in [\tau_{\min}, \tau_{\max}]
\end{align*}
\]
\[
\rho(t) = \begin{cases} 
0.9 \rho(t-1), & \text{if } 0.9 \rho(t-1) \geq \rho_{\text{min}} \\
\rho_{\text{min}}, & \text{otherwise}
\end{cases}
\] (15)

\[
\eta_{ij}(t) = \frac{1}{\lambda_1 \cdot h_y \cdot d_y + \lambda_2 \cdot t_y} = \frac{1}{\lambda_1 \cdot h_y \cdot d_y + \lambda_2 \cdot d_y \cdot h_y \cdot g_y \cdot v_y}, \quad h_y \geq 1, \quad g_y \in [0,1]
\] (16)

\[
w_{ij}(t) = \begin{cases} 
1, & \text{Transport } k \text{ is allowed to pass through arc } (i, j) \text{ at time } t \\
0, & \text{otherwise}
\end{cases}
\] (17)

In the formula, \( q \) is a random variable subject to \( U(0,1) \), \( q \in [0,1] \). \( \tau_{ij}(t) \) and \( \eta_{ij}(t) \) represent the pheromone and heuristic information of \( i \to j \) at time \( t \) respectively. \( \alpha \), \( \beta \) are the importance of \( \tau_{ij}(t) \) and \( \eta_{ij}(t) \) respectively. \( \text{allowed}_k \) is the next optional user set for ant \( k \). \( [\tau_{\text{min}}, \tau_{\text{max}}] \) is the pheromone range on edge \( \text{arc}(i,j) \). \( \rho(t) \) is the Volatilization Coefficient of pheromone, and its starting value is 1.

### 4.2. Algorithmic Steps

**Step 1:** Release ants.
**Step 2:** According to the above improvements, the next node is selected from the ants, and the points that the ants pass through are recorded in the taboo table, and the points are deleted from the table until the ants traverse all the nodes.
**Step 3:** Update pheromones according to Formula (11).
**Step 4:** Check termination conditions.
**Step 5:** Output Optimum

### 4.3. Algorithmic Flow Chart

![Flowchart](image_url)

**Figure. 2 Flowchart of algorithm**

### 5. Example analysis

The warehouse receives a list of requirements. The cluster analysis results show that the distribution network node set is \( \{1,3,4,5,7,8,11,13\} \), which is its hubs. There are 4 vehicles with 1.5 tons of load,
maximum driving distance 500km, average speed 60km/h, unloading speed 5tons/h and 4 available UAVs with weight 20kg/UAV, load 15kg, flight radius 20km, speed 15m/s, unloading speed 0.01h at a time. Vehicles from the warehouse continue to serve users in an orderly manner. When encountering the demand community in the inaccessible area, the vehicle travels to the corresponding distribution node, and then the UAV distribution mode is enabled.

| NO | X  | Y  | q   | ET | LT   |
|----|----|----|-----|----|------|
| 0  | 128| 52 | 0   | 8:00| 14:00|
| 1  | 154| 46 | 6   | 9:10| 9:20 |
| 2  | 90 | 140| 830 | 8:30| 9:00 |
| 3  | 174| 42 | 10  | 9:10| 9:20 |
| 4  | 153| 51 | 4   | 9:00| 9:15 |
| 5  | 164| 47 | 5   | 9:00| 9:10 |
| 6  | 60 | 155| 430 | 10:00| 10:50|
| 7  | 176| 54 | 7   | 9:10| 9:20 |
| 8  | 174| 61 | 8   | 9:00| 10:15|
| 9  | 188| 78 | 300 | 9:00| 9:50 |
| 10 | 170| 87 | 890 | 8:20| 8:50 |

The IAMMAS algorithm is used to solve the above cases in this paper, and the maximum number of iterations is set to 200. The output optimal solution and the algorithm optimization curve are as follows. The specific results of the vehicle and UAV distribution path planning are as follows:

1. Results of distribution network I:
   - UAV1: Mileage 34.138096km, path 11 → 4 → 1 → 13 → 11, time-consuming 0.662187h;
   - UAV2: Mileage 28.530722km, path 11 → 8 → 7 → 11, time-consuming 0.548347h;
   - UAV3: Mileage 38.723071km, path 11 → 5 → 3 → 11, time-consuming 0.737094h;
   - In the network I, the total distribution mileage is 101.391889km, and time-consuming is 0.7371h.

2. Results of distribution network II:
   - Vehicle 1: mileage 201.895609km, route 0 → 2 → 17 → 6 → 14 → 0, time-consuming 3.652927h.
   - Vehicle 2: mileage 210.069179km, route 0 → 10 → 11 → 19 → 0, time-consuming 4.476247h.
   - Vehicle 3: mileage 153.716177km, route 0 → 15 → 20 → 9 → 18 → 0, time-consuming 2.855936h.
   - Vehicle 4: mileage 182.513018km, route 0 → 16 → 12 → 0, time-consuming 3.34188h.
   - The total vehicle distribution mileage in the network I is 748.193983km, and time-consuming is 4.476247h.

To summarize, total distribution mileage is 849.585872km, and total distribution time is 4.4763h in the total distribution network of the vehicle and UAV distribution task, as shown in Figure.3, 4.
Figure 3. Specific path of vehicle and UAV corresponding to optimal solution.

Figure 4. Optimizing Curve

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