A Solution to VRPTW Based on Improved GA-AMMAS Algorithm

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Abstract. Vehicle routing problem with time windows (VRPTW) is a NP difficult problem, and it has important applications in military logistics, especially the distribution of wartime military equipment, materials and spare parts. In the last decade, numerous new methods for VRPTW have sprung up. However, few researches have been made in the study of VRPTW of wartime distribution. Hence, a two-stage solution is proposed in this paper to solve the VRPTW in complex dynamic environment during the war. That is, static route optimization in the pre-planning stage and dynamic route re-planning in the execution stage for sudden or changing enemy threats. An improved hybrid algorithm of Genetic algorithm and adaptive maximum-minimum ant system (GA-AMMAS) is designed in this paper for the solution of the model above.

1. Introduction

Vehicle routing problem (VRP) proposed by Dantzing and Ramser in 1959, is a typical NP-hard problem in combinatorial optimization. As the variant problem of VRP, vehicle routing Problem with time window (VRPTW), is focus and hotspot in the current research of distribution route optimization. A comprehensive study of perfecting the VRPTW’s model and improving its solving algorithm is conducted by a large number of scholars. In terms of model perfection, considering the characteristics of different transportation applications, scholars have constructed a series of more perfect VRPTW models to improve the reliability of the models. For example, the VRPTW problem model with time-varying velocity under uncertain conditions (UTDVRPTW) was proposed by Li et al. [1]; the VRPTW model under the fuzzy time window was studied by Yang et al. [2]; the VRPTW model in congestion situation was considered by Qin et al. [3]; VRPTW model of container loading to be restrained by pallet loading was constructed by Zhang et al. [4]; VRPTW mathematical model of Internet rental car to alleviate the "tide phenomenon" of vehicles was constructed by He et al. [5]; VRPTW problem of logistics support in Plateau area was studied by Ling et al. [6]. In the aspect of solving algorithm improvement, there is numerous the research finding. The research works can be summarized as improvement of a single traditional heuristic algorithm by changing parameters (such as distributed multi-agent ant colony algorithm, improved bat algorithm, improved genetic algorithm, a tissue P system with three cells based MOEA, PDVA)) [7-10] and Improvement by mixing a heuristic algorithm with other algorithms (such as hybrid particle swarm optimization, precise algorithm and the combination of adaptive large-area search algorithm) [11,12].

This paper constructs a wartime vehicle distribution obstacle avoidance path model with mixed time windows in complex dynamic environment, in order to improve the reliability of VRPTW model in battlefield distribution application. In addition, according to the characteristics of the model, an improved genetic algorithm and an adaptive maximum-minimum ant colony algorithm (GA-AMMAS)
is designed to carry out initial path planning. Then, the local vehicle routing is re-planned based on obstacle avoidance strategy to avoid sudden or changing dangerous areas in the distribution area for vehicles carrying out distribution tasks.

2. Description and Modeling of Initial Path Optimization Problem

2.1 Description of Problem

In wartime vehicle distribution routing optimization, the demand is a discrete variable derived randomly, which emphasizes military efficiency, i.e. it has stringent requirements for timeliness and avoidance of enemy threat areas. Departments of decision center designate warehouses to carry out distribution tasks according to real-time information such as demand information (coordinates, demand model, quantity and time window), vehicle status and road condition information and related factors obtained from information platform. Then the distribution vehicle routing of the warehouse is planned to achieve the goal of maximizing the military benefits of the distribution task. Full-loaded vehicles start from warehouse, according to the planned traffic routes, under certain constraints (such as cargo demand, delivery volume, demand time window, vehicle loading limit, maximum driving mileage limit, unit fuel consumption, time limit and actual road condition limit, etc.) serve the combat unit units orderly to maximize military efficiency.

2.2 Model Hypothesis

• Each route of the vehicle starts from its starting point and eventually returns to its initial location.
• The needs of each combat unit must be met, with and only one vehicle to distribute it.
• Each combat unit can only be accessed once.
• At the starting point, the vehicles are all normal vehicles of the same type and are in full oil state, with a total capacity of.

2.3 Model Establishment

According to the above analysis, the mathematical model of VRPTW in wartime distribution is constructed as follows:

$$\min z = w_1 \left\{ \sum_{i \in I} x_{i,j,k} \left( \frac{Q_k - \sum_{e \in \text{arc}_k} y_{e} \cdot d_{e}}{Q_k} \left( \theta_i - \theta_j \right) + \sum_{k=1}^{N} c_{ij} \cdot R_k \right) + w_2 \sum_{k=1}^{N} h_{ij} \cdot d_{ij} \cdot x_{ij} \right\} + w_3 \sum_{j=1}^{J} P_j \cdot y_{j,k}^j \quad (1)$$

s.t.

$$\begin{align}
w_1 + w_2 + w_3 &= 1 \\
w_1, w_2, w_3 &\geq 0
\end{align} \quad (2)$$

$$P_j = \begin{cases} 
(ET_i - t_{j,k}) \cdot M_1(t_i), & t_{j,k} \in (0, ET_i) \\
0, & t_{j,k} = ET_i \\
(t_{j,k} - ET_i) \cdot (LT - t_{j,k}) \cdot M_2(t_i), & t_{j,k} \in (ET, LT) \\
P_0 \cdot (t_{j,k} - LT) \cdot M_3(t_i), & t_{j,k} \in (LT, \infty)
\end{cases} \quad (3)$$

$$\sum_{j=1}^{J} y_{j,k} \leq V_{\text{max}} \quad (4)$$

$$\sum_{j=1}^{J} q_j y_{j,k} \leq Q_{\text{max}} \quad (5)$$
\[
\begin{align*}
    b_j & \leq \frac{1}{n_j} V_{\text{max}}, \forall j \in B \\
    \sum_{i=1}^{K} \sum_{k=1}^{n} x_{ij}^k & = 1, \forall j \in B, i \neq j \\
    \sum_{i=1}^{K} \sum_{j=1}^{n} x_{ij}^k & = 1, \forall i \in B, i \neq j \\
    \sum_{j=1}^{n} x_{0j}^k & = \sum_{i=1}^{n} x_{0i}^k \leq K, \forall k = 1,2,\ldots,K \\
    t_{\text{wait},i,k} & = \max (ET_{i,k} - t_{i,k}, 0) \\
    T_{\text{unload},i,k} & = \frac{q_i}{V_{\text{unload},k}} \\
    t_{i,k} & = t_{i,k} + t_{\text{wait},i,k} + T_{\text{unload},i,k} + t_{\text{unload},i,k} \\
    x_{ij}^k & = \begin{cases} 
1, & \text{vehicle}_j \text{ travel from } i \text{ to } j \\
0, & \text{vehicle}_j \text{ did not travel from } i \text{ to } j 
\end{cases} \\
    y_j^k & = \begin{cases} 
1, & \text{operational unit } j \text{ is distributed by vehicle } B \\
0, & \text{operational unit } j \text{ isn’t distributed by vehicle } B 
\end{cases} \\
    R_k & = \begin{cases} 
1, & \text{vehicle}_k \text{ is used} \\
0, & \text{vehicle}_k \text{ isn’t used} 
\end{cases}
\end{align*}
\]

Where, formula (1) represents the objective function, i.e. the lowest distribution cost, time and penalty cost. Among them, \(d_{ij}\) is the distance, \(v_{ij}\) is the speed, \(b_{ij}\) and \(g_{ij}\) are the correction factors of the above two variables, \(\theta_1\) and \(\theta_2\) represent the unit distance fuel consumption cost under empty and full load respectively, \(Q_k\) represents the maximum load of the vehicle, \(c_{fk}\) is the fixed cost of starting a vehicle. Formula (2) denotes the restriction condition of weight, Formula (3) denotes the penalty cost, \((ET_i,LT_i)\) is the time window, and \(M(t_i)\) is the penalty function. Formula (4-6) denotes the volume, capacity and size limitations of loading, respectively. Formulas (7) and (8) denote that a vehicle needs to leave after visiting a node, and formula (9) denotes that the vehicle starts from the starting point and eventually returns to the starting point. Formula (10) - (12) denotes waiting time, unloading time and arrival time of node j. Formulas (13) - (15) represent 0-1 decision variables.

3. The Design of Initial Path Planning Solution Algorithms

VRPTW is a NP-hard problem. This paper designs a hybrid algorithm for genetic and adaptive Max-Min ant colony systems which has strong global search ability, faster solving speed and higher solving quality, and an adaptive maximum and minimum ant colony algorithm to output the results of initial path planning.

3.1 Improved Fusion Algorithms

Ant Colony Algorithms (ACA), a bionic intelligent algorithm proposed by Dorigo in 1991, has the characteristics of parallelism, positive feedback and strong robustness. It has inherent superiority in solving VRPTW problems. However, ACA has some limitations, such as slow search speed and easy stagnation in the initial stage. After the improvement of a large number of scholars, there are four commonly used ant colony optimization algorithms with better performance: Ant Colony System (ACS), Max-Min Ant System (MMAS), Polymorphic Ant Colony Algorithm (AACA) and Adaptive...
Ant Colony Algorithm (AACA). But the above algorithms are improved from the algorithm itself. Because of the strong robustness of ant colony algorithm, the improvement effect is sometimes not obvious. The research shows that genetic algorithm (GA) has strong searching ability and fast searching speed, which can complement the advantages of ACA, and the performance of the fusion algorithm is obviously better than that of ACA or GA. In this paper, GA and adaptive max-Min Ant System (AMMAS) are improved to balance the simplicity of operation and solution performance.

In solving VRPTW problem with ACA, when artificial ants select the next node, not only the pheromone concentration and heuristic information concentration based on capacity constraints, time window constraints and pheromone concentration, but also the following three aspects should be considered:

- Road quality. Because different road grades, road conditions, congestion levels and enemy attacks correspond to different vehicle driving conditions.
- Time-window-based urgency degree. For example, the priority principle of urgent orders, the priority principle of short waiting time and the priority principle of short time window.
- Actual transportation time. When defining heuristic function in time-varying road network, besides distance, time is also a key factor to be considered.

In summary, inspired by MMAS and ACA, and based on the full consideration of the above factors, this paper proposes the following strategies for selecting the next node in the improved AMMAS:

\[
\begin{align*}
    & j = \arg \max \left\{ \left[ \tau_y (t) \right]^a \left[ \eta_y (t) \right]^b \left[ \delta_y (t) \right]^c \right\} . q \leq q_0 \\
    \tau_y (t + \varepsilon) & = (1 - \rho) \tau_y (t) + \Delta \tau_y (t) \\
    \Delta \tau_y (t) & = \sum_{k=1}^{m} \Delta \tau_y (t) \\
    \tau_y & \in [\tau_{\min}, \tau_{\max}] \\
    \rho(t) & = \begin{cases} 
        0.9 \rho(t - 1), & \text{if} \ 0.9 \rho(t - 1) \geq \rho_{\min} \\
        \rho_{\min}, & \text{otherwise} 
    \end{cases} \\
    \eta_y = w_y (t) & = \begin{cases} 
        1, & \text{vehicle can pass arc} \ (i, j) \ \text{at time} \ t \\
        0, & \text{otherwise} 
    \end{cases} \\
    w_y (t) & = \begin{cases} 
        \sin \left[ \frac{\pi}{2(T_{T_j} - T_j^p)} T_j - \frac{T_j^p}{2(T_{T_j} - T_j^p)} \right], & \text{if} \ t_j < ET_j \\
        \sin \left[ \frac{\pi}{2(T_j^p - 2LT_j)} T_j^p - \frac{T_j^p - 2LT_j}{2(T_j^p - 2LT_j)} \right], & \text{if} \ t_j > LT_j 
    \end{cases}
\end{align*}
\]

where, \( q \) is a random variable subject to \( U(0,1) \); \( q_0 \) is a variation operation parameter, \( q_0 \in [0,1] \); \( \tau_y (t), \eta_y (t), \delta_y (t) \) respectively represent the pheromone content, heuristic information and
satisfaction of combat units from $i$ to $j$ at time $t$; $\alpha,\beta,\gamma$ correspond to importance of each of the above three factors respectively; $allowed_k$ is the next optional combat unit set of ant $k$; $[\tau_{min},\tau_{max}]$ is the pheromone range on edge $arc(i,j)$; $\rho$ is the pheromone volatilization coefficient, and the starting value of $\rho(t)$ is $1$; $\omega_{ij}(t)$ represents whether $arc(i,j)$ at time $t$ can be used by vehicle $k$.

3.2 The Steps of The Algorithm
First, the initial solution of the problem is generated by GA and transformed into the initial pheromone distribution of AMMSA. Then, the optimal solution is obtained by AMMSA. The key to dynamic fusion of GA and AMMAS is to determine the optimal conversion point. The initial pheromone distribution is generated by GA before the optimal point, and the optimal solution is obtained by AMMAS after the point.

Step1: Population initialization. The evolutionary algebraic counter $t\rightarrow 0$ and the maximum evolutionary algebra $Gen_{max}$ are set up, and then a number of $n$ individuals are generated as the initial population $p(0)$ according to the corresponding coding scheme.

Step2: Individual evaluation.
Step3: Selection operation. The selection operator is applied to the group.
Step4: Cross operation. The crossover operator is applied to the population.
Step5: Variation operation. The mutation operator is applied to the population. Population $p(t)$ is selected, crossed and mutated to obtain the next generation population $p(t+1)$.

Step6: Cyclic operations. Firstly, the minimum, maximum number of genetic iterations and minimum evolutionary rate ($Gen_{min}$, $Gen_{max}$, $Gen_{min-impro-ratio}$) of progeny population are set in GA. Then statistical population evolution in the process of statistical iteration. Within the given iteration number range, if the evolutionary rate of successive generations is less than $Gen_{min-impro-ratio}$ the GA process is terminated and AMMAS is entered. Otherwise, $t=t+1$ is transferred to Step2.

Step7: If the termination condition is met, jump out of the cycle. Record the current evolutionary population. According to different fitness functions, different solution sets are obtained.

Step8: Parameter initialization. Initial pheromones of ant colony algorithm are assigned according to the optimal solution of Step7.

Step9: Release ants and determine the set $allowed_k$ of serviceable combat units according to the constraints in the model. Each ant represents a path.

Step11: According to the improved $P^k_{ij}(t)$, ants select the next node from $allowed_k$. Record the point that the ant passes through in the taboo table $tabu_k$, and delete the point from the table $allowed_k$ until the ant traverses all the nodes.

Step12: Update pheromones.
Step13: Check termination conditions.
Step14: Output optimum.

4. Design of Route Re-planning Strategy in Wartime Dynamic and Complex Environment
Consideration of enemy situation plays an important role in wartime VRPTW. Hence, a strategy of vehicle path re-planning in wartime complex dynamic environment is designed by this paper.

4.1 Availability Detection of Locally Preplanned Section
Generally, the enemy radar reconnaissance and bombing area is modeled as a circle, while the forbidden area is modeled as a concave/convex polygon, as shown in Figure 1.
(1) Availability Testing of Path Nodes
The availability of path nodes is judged based on the position relationship between points and graphs. The distance test method is used when the threat area is circular, and the angle test method is used when the threat area is polygon.

(2) Whether the path between requirement nodes passes the test of threat zone
To judge whether the line between two nodes passes through the threatened area, if it does not pass through the dangerous area, the path between nodes is safe, otherwise, it is not available. If the enemy threat area is circular, the intersection point between the path and the threat area is directly judged. If the threat area of the enemy is a polygon, the outsourcing circle strategy is used to judge. To sum up, all of them pass the test of (1) (2), then this local pre-planned section can be used. Threat zone avoidance for unavailable sections.

4.2 Threat Avoidance Strategy
Threat area avoidance strategy, for unavailable \(arc(i,j)\), takes its beginning and end as the local planning path’s start and end point, and generates new sections to avoid the threat area by generating transit nodes. If the new sub-section is still unavailable, repeat the above operation. If trapped in the dead zone, execute the strategy of escape from the dead zone.

Step1: Generate transit nodes. Mark off-point \(G_i\)’s nearest and intersecting threat zone with \(arc(i,j)\). If the threat area is circular, then the safety distance \(d\) is extended from the point \(G_i\) to the circular tangent line, and the transit nodes \(H_1\) and \(H_2\) are obtained from the center connecting the tangent point. If the threat area is polygon, then the safety distance \(d\) of the transit nodes \(H_1\) and \(H_2\) are obtained from the vertex of the intersection point along their respective angular bisectors, as shown in Figure 2.

Step2: Screen secure transit nodes. Eliminate unavailable nodes in Step1. If all the generated points are not available, the transit nodes are re-planned by the route point withdrawal strategy until the initial secure transit nodes are obtained.

Step3: Select the next moving node for \(G_i\) from Step2’s point set, according to the principle of minimizing two-step cost function.

In view of the traditional cost function, one-step optimization idea is adopted, which can easily lead to bypass or fall into dead circle. Therefore, from the perspective of global optimization, the next moving node is selected according to the two-step optimization cost function, as shown in Fig.4, the purple path is the result of one-step optimization and the green path is the path of two-step optimization cost function.

\[
f_{k_1,k_2}(j) = \omega_1 \cdot g_{k_1,k_2}(j) + \omega_2 \cdot h_{k_1,k_2}(j)
\]

\[
g_{k_1,k_2}(j) = |G_i,H_{k_1}| + |H_{k_1},F_{k_1,k_2}|
\]

\[
h_{k_1,k_2}(j) = |F_{k_1,k_2},G_j|
\]
Where \( k_1 = 1, 2, \ldots, N_1, k_2 = 1, 2, \ldots, N_2, N_1, N_2 \leq N_{\text{max}}, g_{h_{k_1}}(j) \) is the distance cost of the pre-generated two-step path from node \( G_j \), and \( h_{k_1}(j) \) is the distance cost of the pre-generated second-step path nodes from \( G_j \).

Step4: Detecting the security of local paths. If \( arc(i, j) \) passes through the threat area, sub-transit nodes are generated according to the above operations, and new local sections are output and detected.

Step5: Dead zone escape strategy. When the threat area is densely distributed, it is easy to form a "dead zone phenomenon", which will cause the path planning to hover repeatedly in this part to form a dead cycle. ①Marking and eliminating the nodes that appear simultaneously in the set of available Pathopen and unavailable points Pathclose. ②Extending from the adjacent vertices of the dead-zone points to generate the dead-zone escape nodes according to the above operations, and adding the nodes that pass the security check and do not belong to Pathclose to Pathopen, as shown in Fig.5.③If the Pathopen table is empty, the dead-zone evacuation method is adopted.

![Figure 3. Dead Zone Escape Diagram](image)

![Figure 4. Sketch of Generating Process of Multilevel Transit Nodes](image)

![Figure 5. Comparison of one-step optimization and two-step optimization path planning](image)

5. Background Cases

Warehouse 0 receives a requirement information sheet, as shown in Table 2. Warehouse 0 currently has five vehicles of the same type with a maximum load of 1000 kg, a maximum driving distance of 800 km and an average speed of 60 km/h. The fleet departs from warehouse 0 at 9 a.m. and returns to warehouse 0. (1) Initial vehicle route planning (2) Local route re-planning based on sudden threat zone.

| NO. | \((X,Y)\)/km | \(q_i/\text{kg}\) | \(ET_i\)/h | \(LT_i\)/h | \(T_{\text{unload}}\)/min | NO. | \((X,Y)\)/km | \(q_i/\text{kg}\) | \(ET_i\)/h | \(LT_i\)/h | \(T_{\text{unload}}\)/min |
|-----|---------------|-----------------|----------|----------|----------------|-----|---------------|-----------------|----------|----------|----------------|
| 0   | (24,0)        | 0               | 9:20     | 17:30    | 0              | 11  | (75.1, 31.1) | 138             | 9:40     | 10:35    | 1              |
| 1   | (9.5,19.6)    | 165             | 9:30     | 9:50     | 1              | 12  | (85.6, 22.2) | 134             | 9:50     | 11:00    | 1              |
| 2   | (0.127)       | 202             | 9:20     | 9:40     | 1              | 13  | (78.2, 10.1) | 107             | 10:00    | 11:00    | 1              |
| 3   | (13.3,35.3)   | 198             | 9:30     | 10:10    | 1              | 14  | (99.3, 15.3) | 176             | 10:00    | 10:30    | 1              |
| 4   | (12.1,34.2)   | 135             | 9:30     | 10:00    | 1              | 15  | (103.1, 7.6) | 168             | 10:00    | 10:40    | 1              |
| 5   | (17.2,31.2)   | 98              | 9:30     | 10:20    | 1              | 16  | (123.2, 4.7) | 137             | 11:30    | 14:30    | 1              |
| 6   | (17.3,26.4)   | 102             | 9:30     | 10:30    | 1              | 17  | (118.5, 17.8) | 128             | 10:20    | 11:00    | 1              |
| 7   | (34.2,22.6)   | 100             | 9:30     | 10:50    | 1              | 18  | (153.4, 24.2) | 119             | 11:10    | 14:00    | 1              |
| 8   | (54.1,15.3)   | 242             | 9:30     | 10:00    | 1              | 19  | (160.7, 30.3) | 114             | 11:00    | 13:30    | 1              |
| 9   | (52.0,29.2)   | 217             | 9:40     | 10:10    | 1              | 20  | (153.0, 31.6) | 112             | 10:30    | 13:00    | 1              |
| 10  | (64.2,36.2)   | 153             | 9:20     | 10:20    | 1              |     |                 |                 |          |          |                |

Let \( m = 1, \alpha = 1, \beta = 5, \rho(0) = 5 \), the solution based on GA-AMMAS is as follows: the initial path planning scheme corresponding to the maximum objective function is as follows.

The path of Vehicle 1 is: \( 0 \rightarrow 2 \rightarrow 1 \rightarrow 4 \rightarrow 3 \rightarrow 5 \rightarrow 6 \rightarrow 7 \rightarrow 0 \)

The route of Vehicle 2 is: \( 0 \rightarrow 8 \rightarrow 9 \rightarrow 10 \rightarrow 11 \rightarrow 12 \rightarrow 13 \rightarrow 0 \)

The route of Vehicle 3 is: \( 0 \rightarrow 14 \rightarrow 15 \rightarrow 17 \rightarrow 20 \rightarrow 19 \rightarrow 18 \rightarrow 16 \rightarrow 0 \)

During the execution of the distribution scheme, the dynamic path re-optimization scheme is shown in Fig. 6, after the sudden enemy threat is known and the threat area is the sum, and the dynamic path
re-optimization scheme is avoided on the basis of closing to the original scheme to the maximum extent.

6. CONCLUSIONS
Aiming at the wartime distribution vehicle routing optimization problem with time windows in complex dynamic environment, this paper proposes a two-stage solution idea of "pre-planning-path dynamic adjustment". In the initial path planning stage, based on wartime factors, this paper constructs a wartime distribution vehicle routing optimization model with time windows in complex environment, and designs a genetic algorithm and a self-adaptive algorithm. The algorithm adapts to the maximum and minimum ant colony algorithm (GA-AMMAS). The validity of GA-AMMAS is verified by SOLOMAN test, and its performance is obviously superior to traditional ACA algorithm. In the execution stage of the distribution scheme, the dynamic re-planning of vehicle subsections is carried out according to the obstacle avoidance strategy after the sudden enemy threat area or the change of the enemy threat area, which improves the practicability of the scheme.

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