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Optimizing Blood Transport Costs: Ant Colony Optimization Method for Vehicle Routing Problem with Time Windows

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Abstract
The Vehicle Routing Problem with Time Windows (VRPTW) is a crucial optimization challenge in logistics, aiming to determine the optimal routes for a fleet of vehicles to service a set of customers within specific time windows. This study addresses VRPTW in the context of blood transportation, where highly reliable and timely delivery is imperative due to the perishable nature of blood products. The purpose of this study is to implement Ant Colony Optimization (ACO) in constructing feasible solutions for blood transportation problem. The ACO algorithm focuses on selecting customers from one node to another without violating distance, time, and capacity constraints until all customers are serviced. After initializing pheromone levels and defining the heuristic information, the algorithm iteratively updates pheromone levels based on the quality of solutions found, enhancing the selection of more optimal routes in subsequent iterations. Programming language is employed to code the proposed algorithm to solve the VRPTW involving large datasets. Extensive simulations are conducted to evaluate the algorithm's performance across different customer distribution patterns, measuring metrics such as total travel cost and adherence to time windows. In this study, three categories of data—cluster, random, and random-cluster data—are used for measuring metrics of different customer distribution patterns. The results show that the ACO algorithm effectively minimizes the total travel cost while ensuring compliance with delivery time windows. The algorithm proves to work across varying numbers of vehicles and customers, consistently producing reliable and timely blood product delivery routes. In conclusion, this study demonstrates the practical applicability of the ACO algorithm in solving VRPTW, particularly for blood transportation problems. The ACO approach not only improves logistics efficiency but also ensures a dependable blood supply chain, ultimately supporting better healthcare delivery.
Keywords: Vehicle Routing Problem with Time Windows; Ant Colony Optimization; VRPTW; ACO

Introduction
Human blood is essential for the body, supplying vital organs with oxygen and nutrients needed for proper function. Blood contains perishable components like platelets (PLTs), red blood cells (RBCs), and plasma, each with different shelf lives [1]. The perishable nature of these components complicates the supply chain (SC), making it challenging to determine the necessary quantities for medical treatments. The unpredictability of blood donation rates further complicates blood supply management [2]. Efficient blood transportation is crucial to ensure that blood products reach their intended recipients on time and in the proper condition. Blood products are time-sensitive and require careful handling and transportation. Delays or inefficiencies in blood transportation can result in life-threatening situations for patients.

The Vehicle Routing Problem (VRP) is a key optimization issue aimed at minimizing transportation costs for a fleet of vehicles from a central depot. The VRP is critical for logistical decision-making regarding location and routing. The Vehicle Routing Problem with Time Windows (VRPTW) extends this by optimizing delivery routes within specific time windows, minimizing total cost or distance. In blood transportation, VRPTW ensures efficient delivery of blood products from blood banks to healthcare facilities, ensuring timely and proper condition of the products [3].

VRPTW is a widely recognized optimization problem in operations research. It focuses on finding the optimal routes for a fleet of vehicles to serve customers within designated time frames, aiming to minimize the total cost or distance travelled. The VRPTW for blood transportation involves the development and testing of various algorithms and methods for solving this problem [4].

A blood delivery routing problem is faced by a regional blood center (RBC). They addressed the Vehicle Routing Problem (VRP) with vehicle time constraints, using a metaheuristic approach to find the most efficient transportation routes. The primary goal was to minimize overall transportation costs. The study developed an algorithm that optimized the blood transport van's route, achieving a significant cost reduction [5]. Moreover, the risks of storing and transporting red blood cells (RBCs) outside recommended temperature ranges, can trigger harmful biochemical reactions. Improperly stored RBCs can lead to serious complications when transfused. A study tracked the temperature of RBC bags throughout the transfusion process, including storage, transportation, and administration. It is concluded that improving blood transportation management from blood banks to hospital wards is essential to prevent adverse outcomes related to blood transfusions [6].

Inefficient blood transportation poses risks to patient health and incurs significant costs. The economic benefits of optimizing vehicle routes in blood transportation, which can save costs and improve healthcare are highlighted [7]. The challenges in blood management, emphasize the need for efficient transport. Studies that consider supply chain costs, time constraints, and emergency severity, help stakeholders make informed decisions for urban blood delivery [8]. Hence, research on the Vehicle Routing Problem with Time Windows (VRPTW) is vital for developing efficient blood transportation methods. VRPTW optimizes delivery routes from blood banks to healthcare facilities, ensuring timely and proper delivery while minimizing costs and distances travelled. A lot of VRPTW cases were carried out in previous studies such as Genetic Algorithms (GA), Simulated Annealing (SA), Tabu Search, and Particle Swarm Optimization [4].

Ant Algorithms are inspired by the behaviour of real ant colonies by their foraging behaviour. The main idea of ant algorithms is the is the indirect communication of the artificial ants based on pheromone trails. A metaheuristic approach, Ant Colony Optimization (ACO), has been proposed which provides a unifying framework of the ant algorithm.

The impact of the Covid-19 pandemic on the management of blood supply chain has become a vital discussion in society. Blood transportation includes several levels in which the material goes through different phases to reach the end customer. This is a health risk especially during the Covid-19 pandemic, while the blood supply is important every time. ACO is used to solve the coordinated effects brought by the Covid-19 pandemic as a blood supply chain with a single blood collection point providing individual blood products and is transported to individual surgical medical centers.

Optimizing vehicle routing problems with time windows (VRPTW) for blood transportation are focused in this study, addressing the unique constraints of time-sensitive and perishable blood products. Ant Colony Optimization (ACO) is used to tackle VRPTW, aiming to improve delivery efficiency for blood transportation. Hence, this research aims to (1) minimize the traveling cost (distance & penalty cost) for blood transportation and (2) constructing a C++ numerical programming for VRPTW and determining the optimal routes for each type of dataset

Literature Review

Supply Chain of Blood Product

The blood supply chain has four steps which are collection, transportation, storage and utilization [9]. The implementation of Movement Control Order (MCO) due to COVID-19 has caused a reduction in the blood supply chain [10]. This is because of the social distancing rules, people have a lower opportunity to donate blood compared to normal times. Hence, the review of the blood collection process such as the collection policy might help during pandemics [11].

Vehicle Routing Problem (VRP)

The Vehicle Routing Problem (VRP) was first initialized because people wanted to find out the shortest route between the station and the trucks such that demand is satisfied where the total mileage covered is minimal [12]. This concept is then expanded into a linear optimization problem and is known as VRP. VRP is to create the most cost-effective delivery routes from a depot to various geographically dispersed customers while adhering to certain constraints [13].

There are various types of VRP based on different constraints. For example, Capacitated Vehicle Routing Problem (CVRP), Distance-Constrained Capacitated Vehicle Routing Problem (DCVRP), Emissions Vehicle Routing Problem (EVRP), Generalized VRP (GVRP), Open VRP (OVRP), Vehicle Routing Problem with Multiple Routes (VRPM), VRP with Pickup and Delivery (VRPPD), VRP with Private Fleet Common Carrier (VRPPC), and VRP with Time Windows (VRPTW) and so on [14].

Capacitated Vehicle Routing Problem (CVRP) is the VRP where the vehicle has a limited capacity. In CVRP, vehicles are subject to capacity constraints, meaning each vehicle can only transport a certain maximum weight or unit of things [15].

Distance-Constrained CVRP (DCVRP) is the extension of CVRP where vehicles have both a maximum carrying capacity and a maximum travel distance. It means that the total distance travelled by each vehicle in the solution does not exceed the maximum allowable distance [16].

Emissions Vehicle Routing Problem (EVRP) has the main objective that is to minimize the emissions and fuel consumption of the vehicle [17].

For Generalized VRP (GVRP), clients are grouped in clusters, and servicing one client implies servicing the entire cluster which is usually used in communication and distribution networks [17].

Open VRP (OVRP) means that routes are open paths to meet customer demand without returning to the depot [17].

VRP with Private Fleet Common Carrier (VRPPC) is also an extension of VRP. In VRPPC, the owner of a private fleet can choose to serve a customer using one of the owner's vehicles or to outsource the delivery to a common carrier [18].

VRPPD is a problem where vehicles must pick up items from specified locations and deliver them to designated destinations. It is quite challenging since it needs to be completed within the required parameters [19].

Vehicle Routing Problem with Time Windows (VRPTW)

The Vehicle Routing Problem with Time Windows (VRPTW) is an extension of the VRP that incorporates time constraints. This implies that vehicles allocated to specific routes must reach their designated destinations within predefined time windows. Currently, applications of VRPTW hold significant importance, as its primary aim is to efficiently deliver specified demands to a set of customers within designated time intervals, utilizing the most cost-effective vehicle routes that commence and conclude at a central depot [20].

Vehicle Routing Problem with Time Windows (VRPTW) involves creating the least-cost routes from a depot to a set of geographically scattered points. Each location must be visited only once by a single vehicle within a specified time window. All routes must begin and end at the depot, and the total demand of all locations on a single route must not exceed the vehicle's capacity [21].

A tabu search method that includes a holding list and a strategy to ensure dense packing within a route is suggested. The concept of penalizing lateness allows for some flexibility in the time windows are introduced [22].

Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) was introduced in the early 1990s, ACO mimics the foraging behaviours of ants, leveraging pheromone trails and heuristic information to efficiently explore the solution space [23].

In the field of blood transportation, applicability of ACO is demonstrated in managing agile blood transport between donor and client sites. The ACO's ability to prioritize urgent deliveries and manage logistics in real-time, showcasing its potential in critical healthcare scenarios are highlighted in the study [24]. Similarly, the optimization techniques in the blood supply chain is reviewed and hence emphasizing ACO's role in handling complexities and uncertainties, thus ensuring timely and cost-effective blood deliveries [25].

Methodology

Research Data

The data in this study is data obtained from the Solomon VRPTW benchmark. Three types of different data are clustered, random and random-clustered. This data will be used as the customer information such as coordinates, demand and time constraints. The *in sample data* and *out of sample data* will be compared to evaluate the accuracy of forecasting results by MAE.

Steps of Ant Colony Optimization Algorithm (ACO)

The ant colony optimization method works as follows:

1) Randomly choose nodes from depot.
2) Find the highest probability nodes from nodes i to nodes j. Check the distance, time and capacity constraints.

$$P_k(i,j) = \begin{cases} \dfrac{[\tau(i,j)]^{\alpha}[\,\eta(i,j)]^{\beta}}{\sum unvisited\ customer[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}} & if\ i \neq j \\ 0 & if\ i\ =\ j \end{cases}$$

3) Update pheromone value

$$\tau(i,j)^{new} = (1-\rho)\cdot\left[\tau(i,j)^{old} + \left(\frac{1}{Distance\ Travelled}\right)\right]$$

4) Find the next highest probability nodes for unvisited nodes and construct a vehicle route.
5) Repeat step 2 until all nodes have been assigned for a vehicle route. The distance travelled d_{ij} between customer i and customer j will be calculated by using Euclidean distance

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}$$

6) Construct the final solution.

Formulation of the VRPTW Model

A model for VRPTW for a single depot is formed, the depot is assigned as an origin, includes a group of customers with known demands, D, a homogeneous fleet of vehicles with fixed capacity, Q, and penalties will given if early arrival or late arrival occurred. Below is the model formed,

Decision variables:

$$X_{ij}^{p} = \begin{cases} 1 & if\ vehicle\ p\ travels\ from\ customer\ i\ to\ customer\ j \\ 0 & Otherwise \end{cases}$$

t_i

The objective is to minimize total penalty cost and

$$\sum_{p=1}^{P}\sum_{i=0}^{N}\sum_{j=0}^{N} C_{ij}^{P}\, X_{ij}^{P} \tag{1}$$

Subject to

$$\sum_{p=1}^{P}\sum_{i=0}^{N} X_{ij}^{p} = 1 \qquad j = 0,1,2, \ldots, \mathrm{N} \tag{2}$$

$$\sum_{j=1}^{N} X_{0j}^{P} \leq 1 \qquad p = 1,2,3, \ldots, \mathrm{P} \tag{3}$$

$$\sum_{i=1}^{N} X_{\mathrm{ij}}^{P} \leq 1 \qquad p = 1,2,3, \ldots, \mathrm{P} \tag{4}$$

$$\sum_{j=0}^{N} D_j \left(\sum_{i=0}^{N} X_{ij}^{P}\right) \leq Q \qquad p = 1,2,3, \ldots, \mathrm{P} \tag{5}$$

$$a_i \leq t_i \leq b_i \qquad i = 1,2, \ldots, N \tag{6}$$

From the formulation presented, the objective function (1) aims to minimize the total cost (i.e., distance) covered by all the vehicles used. Equation (2) ensures that each customer is served exactly once. Equations (3) and (4) require that each customer is served by only one vehicle. Additionally, equation (5) ensures that the total demand of the customers assigned to each vehicle does not exceed the vehicle capacity Q. Finally, equation (6) guarantees that the service start times for each customer fall within their specified time windows.

Ant Colony Algorithm for VRPTW

The ACO applied in VRPTW follows:

1) Initialization

   Define the VRPTW parameters: customers, time windows, vehicle capacities, and depot. Initialize artificial ants, usually one per vehicle. Randomly choose nodes from the depot.

2) Ant Movement

   Each ant starts at the depot and selects the next customer based on probabilistic rules. Check capacity and time window constraints before adding a customer to the route. Continue until all customers are visited or no feasible customer can be added.

3) Pheromone Update

   Perform a local pheromone update after each ant constructs its route. Intensify the attractiveness of recently visited edges to promote exploration of good solutions.

4) Iteration

   Repeat the movement and pheromone update steps for a set number of iterations or until a termination criterion is met. Ants construct solutions, update pheromones, and explore the search space.

Results and discussion

Cluster Data

A cluster data set is used for running the ACO method. The data set reflects scenarios where residents are densely populated, resembling urban areas. Hence, this dataset will be employed to investigate the Vehicle Routing Problem with Time Windows (VRPTW) in densely populated regions. The objective is to ensure that each vehicle efficiently fulfills customer demands while adhering to capacity and time constraints.

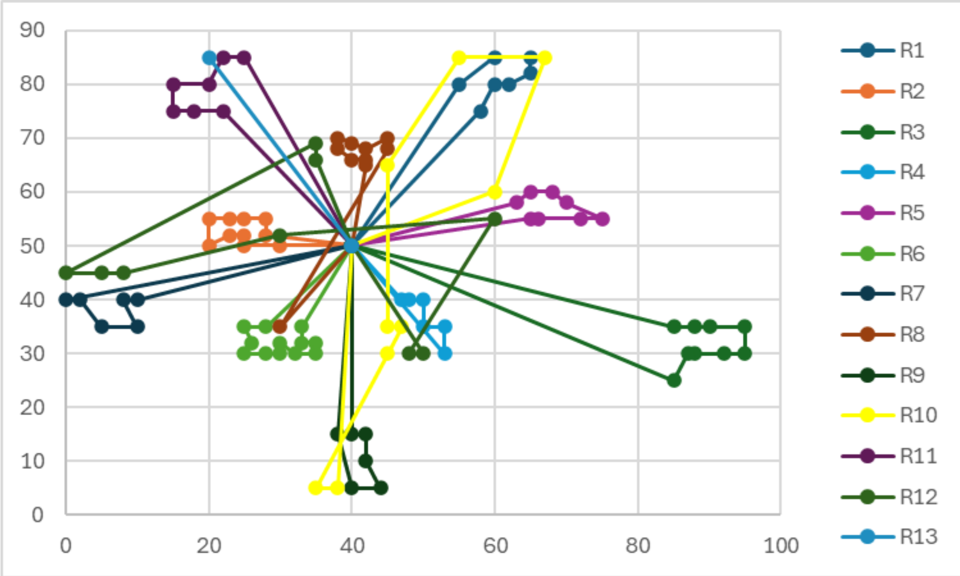

Figure 1 Feasible solution for clustered data

Based on the plot in Figure 1, the route constructed seems to be quite oriented as the hospitals are clustered. Hence cause a higher total traveling cost and penalty cost. The optimal solution consists of 13 routes and all of them start and end at the depot. This shows that hospitals will not to pay too high for transportation fees to carry out blood transportation.

Random Data

The meaning of random refers to events or selections occurring by chance rather than by design or planning. In this study, the random dataset represents rural areas where hospital build lack of planning. Given that the destinations of hospital in rural areas are far apart, customer demands are usually low. Thus, the random dataset serves to explore the Vehicle Routing Problem with Time Windows (VRPTW) in rural areas, addressing capacity and time constraints.

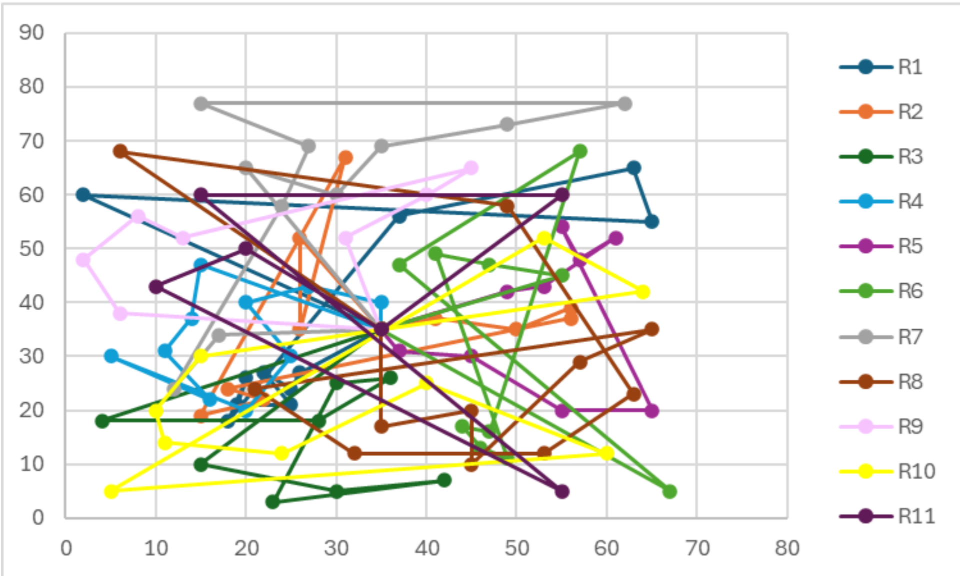

Figure 2 Feasible solution for random data

Based on the plot in Figure 2, the route constructed seems to overlap and hence cause a higher total traveling cost and penalty cost. The optimal solution consists of 11 routes and all of them start and end at the depot. This shows that hospital will have to pay higher to carry out blood transportation in rural areas as there might built far apart from each other.

Random Cluster Data

Random-clustered data often characterizes developing regions or major cities where facilities are readily available. These areas play a vital role in improving healthcare growth. The random-clustered dataset employed in studying the Vehicle Routing Problem with Time Windows (VRPTW) comprises 100 customers and a single depot. Therefore, this dataset serves as a fitting representation of developing areas aimed at increasing healthcare services.

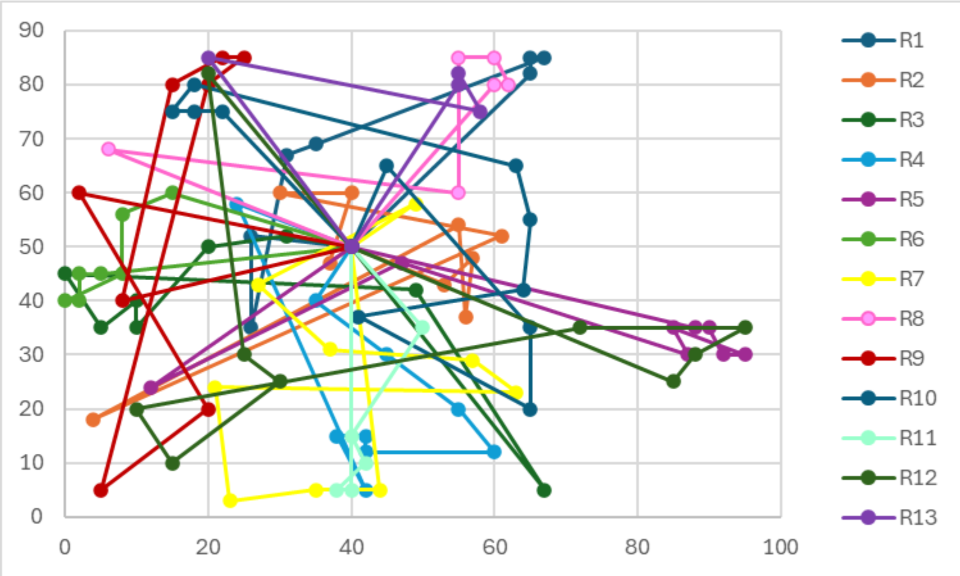

Figure 3 Feasible solution for random cluster data

Based on the plot in Figure 3, the route constructed seems to overlap and hence cause a higher total traveling cost and penalty cost. The optimal solution consists of 13 routes and all of them start and end at the depot. This shows that Hospital will have to pay higher to carry out blood transportation in developing areas.

Comparison

The results of three different data sets to solve VRPTW using the ACO provided in Table 1.

Table 1: Comparison of results between three different data

	Clustered	Random	Random Cluster
Maximum Capacity (units)	150	150	150
Number of Routes	13	11	13
Average number of customer	8	9	8
Total Distance (units)	1281.35	2249.71	2437.27
Total Penalty (units)	5644	9936	6315
Total Overall Cost (units)	6925.35	12185.71	8752.27

Based on Table 1, the random data has the least number of routes compared to the clustered data and random cluster data. The random data set has the highest average number of customers per route (9), while clustered and random cluster data sets have an average of 8 customers per route. Besides, the total distance traveled is the lowest for clustered data because the customers are distributed by clustered and this will reduce the distance travelled from customer i to customer j. Total distance traveled is the highest for random cluster data, followed by random data.

Furthermore, a penalty will be given for early or late arrivals, this is due to the perishable nature of blood product. Hence, other than the travel cost, penalty cost influences more to the total overall cost. Based on Table 4.10, the total penalty of clustered data is the least, followed by random clustered and random data. The high penalty of random data indicates that the distribution of random data faces more challenges in meeting time windows.

Lastly, for total overall cost, the random data set has the highest overall cost, which is significantly higher than the costs for clustered and random cluster data sets. The clustered data has the lowest overall cost. These results show the variations in routing efficiency and costs depending on the distribution of customers, with clustered distribution leading to more optimal solutions in terms of distance and overall cost.

Conclusion

Some conclusions are shown in this research. First, the optimal vehicle capacity depends on balancing the minimization of distance travelled and controlling penalties. This is because the overall cost comprises both travel costs and penalty costs. Based on the result we obtained in the previously, minimize number of routes may not help in minimizing the total overall cost. Additionally, the total number of routes constructed and the total distance traveled are influenced by the value of distance constraints. This is because the selection of customers for each route is conducted by considering the probability that involves distance in the calculations. Moreover, increasing vehicle capacity reduces the number of routes but leads to higher penalties. This results suggests that when the route are operated with fewer route using vehicles with larger capacity, it may not be optimal if it results in significantly higher penalties due to early arrival and late arrival.

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