Vehicle Routing Problem Machine Learning Solution for Package Delivery/Pickup

By Jai Keerthy Chowlur Revanna & Nushwan Yousif B.Al-Nakash (PhD) 
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GJCST-D Classification: F.1.1

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I. Introduction

Transportation is one of the primary requisites of civilization and this fact continues to be true even today. In today’s world of quick and safe deliveries, there has been a need for better service, reduction of vehicles used, maximizing profit, reduction in travel time variation and reduction of overall travel cost. To define these problems together, the term Vehicle Routing Problems was coined. This problem deals with the supply chain of an organization. Transportation is the backbone of the logistics of any organization and it takes up about 40 to 50% of the total logistics cost, as stated by Cogoport (accessed on 11 October, 2021). This includes international and domestic transport, customs, all modes of transport such as air, water, land and so on. It can be inferred that transportation cost is a major and important factor in the supply chain of an organization, so its cost optimization becomes a necessity. The logistics branch of the organization must work on the management of transportation, deliver within customer provided time frames, competing with other organizations for better service and service rates effectively, handling unpredictable events and so on. The world is witnessing the digital growth spur and along with its influence on almost every sphere of life and nature. Integration of logistics and e-business will be a fruitful endeavour. This incorporation will lead to improvement in customer service, tracking, deliverance, time effectiveness as well as reduction in the overall cost. Looking at the technical aspects of the VRP, there are initially p vehicles at the depot which must carry different amounts of supplies to q customers. Now, the VRP will aim to discover the optimized route that for vehicles/groups delivery/pickup services. This way a standard solution is obtained which contains every route that begins and finishes at the depot, with the constraint that the goods are delivered within or before the time range set by the customer, its limit and it considers the working time of the drivers. This paper will discuss how the Ant Colony Optimization (ACO) with K-Means Clustering [1], [2] (ACO-K-Means) has been employed to minimize costs when doing package delivery from depot to the customer within or before the time frame constraint set. The mathematical model defined in this paper will tackle and solve the problems related to distribution, e-logistics, retail networks and so on.

Dantzig and Ramser [3] were the ones to first introduce the Vehicle Routing Problem in 1959. Their solution was based on linear programming. It was a truck dispatching problem that dealt with the delivery of gasoline at gas stations. Later, [4] Clarke and Wright came up with the savings method and it was termed as the Clarke-Wright algorithm. Their practical methodology gave better results than the Ramser-Dantzig algorithm. This was because the latter algorithm simply linked the customer pairs that were close to each other, which means that only distance constraint was considered, while the former not only considered the distance constraint, but they also reduced the distance rather than linking the two customers to different routes. Fast forward to 1992, Daskin and Malandraki came up with the time dependent vehicle routing problem (TDVRP) [5]. Then another solution was introduced by Ichoua et al. [6] which had a step function along with a piecewise linear function of time distribution which was fulfilling the FIFO (first in first out) principle, which was defined by Ahn et al. with this, several researches and studies popped up. Some were utilizing route construction savings method and an insertion approach to solve incapacitated TDVRP (with/without time windows), some had heuristic solutions [7], [8], [9], some metaheuristic algorithms [10], [11], [12] and others hyper heuristics [13].

Figure 1. given below is a generalized view of how a VRP is solved.
This paper has five sections in total. Section 1 deals with the introduction while section 2 deals with the literature survey. Section 3 handles the mathematical model of the proposed system [ACO using K Means Clustering Algorithm], section 4 will explain the approach to the solution, section 5 will have the results and case studies, with section 6 concluding the paper.

II. Literature Survey

One of the heuristic solutions mentioned was provided by Hideki Hashimoto, Mutsunori Yagiura and Toshihide Ibaraki[7]. In their paper they generalized VRPTW by making travelling costs and duration to be time-dependent functions. They used local search algorithm to find the vehicle routes and using that, evaluated a neighbourhood solution. They proposed an algorithm that could efficiently pick optimal routes using data from previous dynamic programming recursion that were utilized to assess the current arrangement. They even included a filtering strategy that determines which spaces in the neigbourhood are not to be searched so as to avoid dead ends in improving the solution. They finally conclude with a local search algorithm that combines all their modifications.

A metaheuristic solution was proposed by Yiyu Kuo[11]. In the research paper, the author has considered fuel utilization and CO2 emission as the constraints to the Time-Dependent Vehicle Routing Problem (TDVRP). The paper has proposed an algorithm that determines a route that consumes less fuel and has the least carbon emissions. With this algorithm the author was able to provide an overall improvement of 22.69% in minimizing transportation distances and 24.61% improvement in fuel consumption.

[13] has used a two-phase method that includes Genetic Algorithms along with Random Search incorporating simulated annealing concepts to tackle the time dependent vehicle routing problem (TDVRP). This is a hyper heuristic solution.

Paper [16] has taken into consideration the problems of carbon pollution and environmental issues. Electric vehicles were considered to reduce the various problems mentioned but it brought along with it the issue of charging locations and battery capacity. To tackle these problems, a new variant in the classical VRPTW was brought about which integrated the ideas of multiple charging points that also have the facility of swapping batteries. The authors proposed a mixed integer programming model to tackle the issue using the advanced ACO algorithm with hybridised insertion heuristics and enhanced local search.

Another reference has been taken from [17] which is quite close in similarity with this paper’s solution. The problem that the paper addressed was that deliverance of perishable goods within a given time frame was a daunting task and if unexpected events took place, the extremely important goods would not reach their destination, leading to a molehill of problems and difficulties. The authors Yao Wu, Bin Zheng and Xueliang Zhou have proposed a working model where the possibility of disturbance the board has been utilized to make an interruption recuperation model with an alternate kind split conveyance that is utilized for between course response dependent on a past TDVRPTW. It considers the idea of transient merchandise and dynamic travel course decision in big cities. The, a tabu search algorithm is brought up to create a solution for the initial routing problem. This will be further stretched out to make the disturbance recuperation plan.

[18] Researchers have also used a novel ant colony optimization algorithm based on improved brainstorm optimization (IBSO-ACO) to tackle VRP with delicate time windows. As per this paper, the traditional insect settlement calculation has been changed to productively take care of the nearby ideal issue.
Their exploration has given evidence that it can accomplish a lower directing expense at a high union rate than the classical ant colony (ACO) and the stimulated annealing ant colony algorithms.

Looking into other heuristic strategies involved, [19] has the space-filling curve with optimal partitioning as a solution while another has three-phase heuristics which has been developed by grouping a heuristic-based clustering algorithm solving VRP [20]. Summary of other important state-of-art modern heuristics is available in [21], [22].

In this work, a VRP with Time Widows constrains is used to modify ACO with K-Means clustering. Ants use pheromones to leave behind a trail for its comrades so as to use the optimal path fixed to reach the food source. There has been several research based on this behaviour of ants, such as [23], which was the first paper to be published on this topic. Papers [24], [25], [26], [27], [28], [29] have various hybrid versions of ACO in varied fields.

Using this behaviour of ants and with the help of previous research work based on a somewhat similar problem, this paper aims to solve VRPTW using the K-Means Clustering algorithm to find the most optimal path to the customer.

III. Mathematical Model Of Proposed System

This part will use certain terms and elements from [26]. It is a case study based on VRPTW regarding fresh food distribution centres. There will be two subsets of service nodes: pickup set $P_S$ and delivery set $D_S$. The values of these terms are $|P_S| = x$ and $|D_S| = y$ respectively. Now, starting depot node is set to 0 and end depot is set to (x+y+1). A node will be replicated if it needs both delivery and pickup. Each vehicle has its set capacity and operation cost. In case there is a request between pickup hub $m$ and delivery node $n$ then there will be a set $R$ which contains pairs of (m, n) [30].

Looking at the objective function that reduces total travelling cost, the equation is as follows

$$\min \sum_{k \in K} \sum_{m,n \in C} p_{mn}^k \tau_{mn} \mu_k$$

Here, $K$ refers to Cluster number and $C$ denoting the centroid of clusters.

$$\sum_{k \in K} \sum_{n \in C} p_{mn}^k \geq 1 \forall m \in C \setminus \{0, x + y + 1\}$$

Equation 10 shows time constraint while 11 shows capacity bound constraint.

$$\sum_{n \in C} p_{an}^k - \sum_{n \in C} p_{nm}^k = 0 \forall k \in K, \forall (m, n) \in R$$

A vehicle must pass starting and ending depots at least once and this is shown by equations 4 and 5

$$\sum_{n \in C} p_{mn}^k \leq 1, \forall k \in K$$

$$\sum_{n \in C} p_{mn}^k, x+y+1 \leq 1, \forall k \in K$$

If a vehicle reaches a node, it must leave it as well. This is shown in equation 6.

$$\sum_{n \in C} p_{mn}^k - \sum_{n \in C} p_{nm}^k = 0, \forall n \in C \setminus \{0, x + y + 1\}, \forall k \in K, o \neq m, n \neq m$$

Equations 7 and 8 have integrated time constraints, subtour elimination and load constraints.

$$T_{cdn}^k + (t + mn + sm) - B(M_{1} - p_{mn}^k) \leq T_{cdn}^k$$

Now, if there is an order placed between two nodes and first the pickup node and then the delivery node will be visited then equation 9 shows it.

$$T_{cdn}^k \geq R_{mn}(s + t) + T_{cdn}^k$$

Equation 10 shows time constraint while 11 shows capacity bound constraint.

$$l_m \geq T_{m}^k \geq f_m \forall m \in C \setminus \{0, x + y + 1\}, k \in K$$

(A_k + d_m, A_k) \geq L_m \geq (0, d_m), \forall k \in K, m \in C$$

Now showcasing the constraint of limiting number of vehicles used and maximum working duration in equations 12 and 13.

$$\sum_{k \in K} \sum_{n \in C} p_{mn}^k \leq M$$

$$t_{max} \geq T_{m}^k \geq T_{max}^k$$

This mathematical model is a small-scale solution.

IV. Implementation Hardware and Software

Hardware: System Pavilion X-360 Convertible 15-Crx000
Processor: Intel core i-130 CPU 2.20 GHz, 2208 MHz
Software: Python 3.9.7 and PyCharm community edition 20.1.1

V. Approach to The Solution

In this paper, the Vehicle Routing Problem with Time Window (VRTPW) requirement has been settled using a modified version of the Ant Colony Optimization using KMeans Clustering. Marco Dorigo was the first person to introduce Ant Colony Optimization, in the 90s,
in his Ph.D. thesis. The solution calculation depends on the conduct of ants, the way they live in colonies and search for food. While an ant goes around, searching for food, it leaves behind pheromones that act as a beacon. It acts as a communication mechanism and each time the ant leaves a pheromone trail, it tells the other ants about the quality and quantity of food the former ant had been carrying. This way, there are several set paths that the ants use based on the number of pheromones released in a path. The shortest and fastest route is chosen for maximum traffic. Ant Colony Optimization (ACO) algorithm is a probabilistic procedure dependent on the above peculiarity to track down the ideal path. With the inclusion of K-Means Clustering, this modified approach has solved the constraints of the MPMDVRPTWHF, which has resulted in shorter time consumption, delivery within the time window and lower transportation costs along with the inclusion of multiple pickup and delivery nodes where in a pickup point might or might not have multiple delivery locations. The flowchart below showcases the solution setup.

Fig. 2: Flowchart showing the proposed solution

a) Parameter Initialization
Looking at the research done in [26], the following parameters are set as follows: Number of ants $z = 22$, $\alpha = 2$, $\beta = 5$, $\rho = 0.80$, $\theta = 80$, elitist ants $\sigma = 3$. In the graph $G = (N, A)$, each arc $(m,n)$ has been assigned a variable called pheromone trail $\tau_{mn}$. The probability of better solution is directly proportional to the pheromone intensity. This means that when an ant wants to go to another node from its current node, it will choose the one with the maximum pheromone intensity. To make this work, a fixed quantity of pheromone is allocated to every arc. To decide which node to proceed to (node $n$), the $k$th ant will use the pheromone trail $\tau_{mn}$ which is showcased below:

$$u_{mn}^k = \frac{[\lambda_{mn}]^\alpha [\tau_{mn}]^\beta}{\sum_{l \in N_m} [\lambda_{ln}]^\alpha [\tau_{ln}]^\beta}, \text{if } n \in N_m$$

(14)

Initially, all probabilities are set to 1. $\lambda = \frac{1}{z}$ is a heuristic value, pheromone concentration on the edge when the ant travels from node $m$ to node $n$ is denoted by $\tau_{mn}$ and relative impact of the pheromone focus, and the heuristic worth is shown by $\alpha$ and $\beta$. If we go into the specifics, then $\lambda_{mn}$ denotes how much favourable is the next node $n$ while $\tau_{mn}$ implies how much better is the next node relatively.

b) Solution Construction
In this scenario, the solution is generated when an artificial ant takes vehicles from the vehicle set and constructs a path, starting from the warehouse or depot, by choosing those nodes that satisfy the set of constraints. The ant continues to build the route until the cutoff of route length has been reached or when the time window imperative has been resisted. In this way, in framing the course, the ant will check every node whether it satisfies every one of the imperatives and if it tracks down such a node, it will append it to the route, update the variables and go for the next node, using the updated variables. These changes in each iteration are all recorded in an answer set, which will then, at that point, be utilized for tracking down good solution BS from the set.

When determining the optimal route for the best solution, pheromone update is used which includes pheromone deposition and pheromone evaporation. Pheromone update is used to elevate the pheromone values that are found on good solution paths and decrease those that are on bad solution paths. In pheromone deposition and evaporation, pheromone values either increase or decrease at a constant rate [31].

The pheromone evaporation equation is given as such,

$$\tau_{mn} = \tau_{mn} \left(1 - \frac{\theta}{S_{avg}}\right), \quad \forall (m, n) \in A$$

(15)

Where trail persistence $1 \geq \rho \geq 0$ of the evaporation factor $1 \geq \left(\frac{\theta}{S_{avg}} + \rho\right) \geq 0$ and $\theta$ is a constant. In each iteration, $z$ number of ants find $S_{avg} = \frac{\sum_{b=1}^{z} S_b}{z}$ of average total distance. Then pheromone is updated by the elitist and best ants After the evaporation process, it chooses the fittest ants can refresh the pheromone deposits, signifying the optimal path to be chosen, as seen in the equation [18]

$$\tau_{mn} = \tau_{mn} + \Delta \tau_{mn} + \sum_{b=1}^{z} \tau_{mn}$$

(16)

Where,

$$\Delta \tau_{mn} = \left(\frac{\sigma - \lambda}{S} \right)$$

(17)
if $\lambda^b$ best ant travels on edge $(m,n)$ 0 otherwise

$$\Delta \tau_{mn}^* = \left\{ \begin{array}{ll}
\sigma_{BS} & \text{if } \lambda^b \\
0 & \text{otherwise}
\end{array} \right.$$

Looking at equations 17 and 18, it can be concluded that there are two types of pheromone depositions that are deposited on the trails during the pheromone update process. First, if $\sigma$ elitist ants have travelled a path, that path will be updated as the best solution so far (BS), in accordance with the ACO+KMeans Clustering algorithm. $\Delta \tau_{mn}^*$ denotes the pheromone update by the elitist ants. Second, out of the $z$ ants available, only $(\sigma - 1)$ best ants, in the current iteration, can deposit pheromone on the path they have already travelled. The term $\Delta \tau_{mn}^*$ is used to denote the pheromone quantity laid down on the trails that have been traversed by them and the amount of pheromone that have been deposited by the ants are determined by their solution quality $S^A$ and rank $\lambda$ and the value is equal to $\Delta \tau_{mn}^*$. To summarize, the elitist ants need to increase the probability of the best-solution so far after each iteration as the values that are updated will act as reference values for the next iteration. The ranking methodology has been employed in [19] so as to reduce pheromone deposition on those routes that have relatively lesser favourability.

VI. Case Study

a) Dataset Used

The dataset for this paper has been taken from the Solomon-100 standard test set which have 20 problem cases. It also includes x-y location coordinates, service time, demand by customers, due dates, and ready time. This section will be in comparison with [32] as it has used the same data set. This comparison will help in proving that the proposed solution from this paper is the better method of solving the (MPMDVRPTWHF) as it gives better cost reduction with lesser percentage of carbon emissions, along with optimized fuel consumptions and lesser vehicles used.

b) Parameters Defined

The parameters defined in this paper are derived from “Cold Chain Logistics Path Optimization via Improved Multi-Objective Ant Colony Algorithm,” [32] as this paper is in comparison with the latter. Similar to [32] the delivery vehicle used is a refrigerator car and the set of pre-defined parameters are given table I below.

c) Result Analysis

The entire result section has used the Pareto optimal principle for obtaining the solution. The Pareto Principle shows that venture’s advantage of 80% is an outcome 20% of the work. The optimal version of it makes the sub objectives suppressed so as to efficiently solve the main objective. Due to this there is very little scope of conflict of objectives from the sub objectives and a noiseless solution is obtained. Referring to [32], this paper the objectives chosen will be carbon emission reduction, total cost, time frame and customer satisfaction.

<table>
<thead>
<tr>
<th>Table 1: Parameters, Implications, and Its Preferred Value</th>
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</thead>
<tbody>
<tr>
<td>Parameters</td>
</tr>
<tr>
<td>------------</td>
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<tr>
<td>$g$</td>
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<tr>
<td>$P$</td>
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<tr>
<td>$\Delta T$</td>
</tr>
<tr>
<td>$\lambda$</td>
</tr>
<tr>
<td>$t_e$</td>
</tr>
<tr>
<td>$\delta$</td>
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<tr>
<td>$c_1$</td>
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<tr>
<td>$c_2$</td>
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<tr>
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<td>$\rho$</td>
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<tr>
<td>$\sigma$</td>
</tr>
<tr>
<td>$\tau_{min}$</td>
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<tr>
<td>$\tau_{max}$</td>
</tr>
<tr>
<td>$w_1, w_2, w_3$</td>
</tr>
<tr>
<td>$K$</td>
</tr>
<tr>
<td>$h$</td>
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<tr>
<td>$S$</td>
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<td>$\psi$</td>
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<tr>
<td>$T$</td>
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<tr>
<td>$L$</td>
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</tbody>
</table>
Using several test cases of 25, 50, 75 and 100 customers in three different scenarios, the proposed ACO algorithm with K-Means clustering provides a better solution in comparison. The results are arranged in the Pareto optimal solution format. The test cases and their outputs are given below.

Table 2: Legend

<table>
<thead>
<tr>
<th>CNY</th>
<th>Cost in CNY</th>
</tr>
</thead>
<tbody>
<tr>
<td>CE</td>
<td>Carbon Emissions</td>
</tr>
<tr>
<td>CS</td>
<td>Customer Satisfaction</td>
</tr>
<tr>
<td>NV</td>
<td>Number of Vehicles Used</td>
</tr>
</tbody>
</table>

i. c.i. No. of Customers - 25

C101 (25) test table is used here for obtaining the most optimal path with better results of the constraints set. This solution has used the Pareto optimal approach and figure 3 has shown the comparison between [5] and this paper. It is clearly visible from the graph that the proposed algorithm of ACO+KMeans (PS KPSO) clustering has better output in terms of carbon emission, customer satisfaction and total transportation cost.

Fig. 3: c101 (25) comparison with [32] (ACOMO) and ACO+KMeans Clustering (PS KPSO)

PS KPSO algorithm has given total cost as 3138.07, lower carbon emission of 19.50 and 100 percent customer satisfaction in all cases. The trucks used is 3 with respective optimal travel paths (0, 5, 3, 7, 8, 10, 11, 9, 6, 4, 2, 1, 0), (0, 13, 17, 18, 19, 15, 16, 14, 12, 0) and [(0, 20, 24, 25, 23, 22, 21, 0).

ii. c.ii. No. of Customers - 50

This part has used the c101 (50) test table. 5 trucks have been employed with respective paths (0, 43, 42, 41, 40, 44, 46, 45, 48, 51, 50, 52, 49, 47, 0), (0, 5, 3, 7, 8, 10, 11, 9, 6, 4, 2, 1, 75, 0), (0, 32, 33, 31, 35, 37, 38, 39, 36, 34, 0), (0, 67, 65, 63, 62, 74, 72, 74, 61, 64, 68, 66, 69, 0), (0, 20, 24, 25, 27, 29, 30, 28, 26, 23, 22, 21, 0), (0, 57, 55, 54, 53, 56, 58, 60, 59, 0), (0, 13, 17, 18, 19, 15, 16, 14, 12, 0) and (0, 71, 70, 73, 0). The final results of carbon emissions, total cost and customer satisfaction are 54.96, 10639.71 and 100 percent respectively. Figures 7 and 8 showcase the comparison between [27] and this paper and the route distribution of the vehicles.

iii. c.iii. No. of Customers - 75

The c101(75) dataset has been used in this part. The number of vehicles used is 8 with the most optimal paths chosen respectively: (0, 43, 42, 41, 40, 44, 46, 45, 48, 51, 50, 52, 49, 47, 0), (0, 5, 3, 7, 8, 10, 11, 9, 6, 4, 2, 1, 75, 0), (0, 32, 33, 31, 35, 37, 38, 39, 36, 34, 0), (0, 67, 65, 63, 62, 74, 72, 74, 61, 64, 68, 66, 69, 0), (0, 20, 24, 25, 27, 29, 30, 28, 26, 23, 22, 21, 0), (0, 57, 55, 54, 53, 56, 58, 60, 59, 0), (0, 13, 17, 18, 19, 15, 16, 14, 12, 0) and (0, 71, 70, 73, 0). The final results of carbon emissions, total cost and customer satisfaction are 54.96, 10639.71 and 100 percent respectively. Figures 7 and 8 showcase the comparison between [27] and this paper and the route distribution of the vehicles.

iv. c.iv. No. of Customers - 100

This section has used the c101 (100) dataset. Now looking [32], there are better results in terms of carbon emission, cost and customer satisfaction (69.03, 13561.41 and 100 percent). Instead of 23 vehicles, 10
Figures 6 and 7 illustrate the vehicle distribution routes for cases with 50 customers (c101(50)) and 75 customers (c101(75)) respectively. The figures show the optimal paths chosen by the proposed ACO+KMeans clustering algorithm.

Figures 8 and 9 compare the proposed ACO+KMeans clustering algorithm with [32] (ACOMO) and ACO+KMeans Clustering (PS KPSO) for cases with 75 and 100 customers (c101(75) and c101(100)). The proposed algorithm shows improved performance in terms of cost and carbon emissions.

The comparison (Figures 10) highlights the effectiveness of the proposed ACO+KMeans clustering algorithm with [32] (ACOMO) and ACO+KMeans Clustering (PS KPSO) for cases with 100 customers (c101(100)). The proposed algorithm demonstrates a significant reduction in total costs and carbon emissions, along with high customer satisfaction.

Looking at all the results, it is evident that the ACO+KMeans clustering algorithm outperforms the improved Ant Colony algorithm [12] and the normal Ant Colony Algorithm [28]. With fewer vehicles employed, lower carbon emission levels, and better cost management, the proposed system has shown its effectiveness and viability for real-world logistics problems. The proposed algorithm PS KPSO has provided about 10.37%, 46.9%, 61.98%, and 78.81% reduction in total costs for 25, 50, 75, and 100 customers respectively. Along with the aforementioned improvements, there is 100% customer satisfaction in all cases.
(ACO+KMeans Clustering) has outperformed the Modified Ant Colony Algorithm and the original Ant Colony algorithm. Table III analyses the consequences of the proposed calculation and modified ant colony algorithm.

e) Results with other test cases

In the Solomon-100 dataset, there are three formats of destination grouping. One is a cluster format (C), one is a random format (R) and one is a random-clustered format (RC). These three formats have been used for 25, 50, 75 and 100 customers. So other than C101, there are C201, R211, R201 and RC201. The comparison between the proposed algorithm (ACO+KMeans algorithm) and modified Ant Colony algorithm [32] have been given in Table IV.

The data from Table 4 helps in evaluating the viability of the proposed algorithm. Even with increase in the number of customers, be it clustered, random or both, there is barely any increase in the number of vehicles employed. With an average of 2.625 vehicles per case, this greatly affects the total travel, storage, damage and fuel costs while reducing the carbon footprint by a great extent, ultimately helping not only the economy of the organisation but also trying to improve the environmental condition of the Earth. It can be assumed from the results data that there is a high probability of increase in customers. As the vehicle used reduces, there is scope of increasing customer reach and maybe there is a chance of increasing the speed of delivery. With the new electronic vehicle usage, there will be even more cuts in the carbon footprint value and better customer coverage. In the above results display and visualizations, using the Solomon benchmark each of them gradually increased. Averaged results of 6 different Solomon categories using multiple variants with 15% and 55% dynamicity which has shown both for capacity and route.
**Table 3:** Comparison between Algorithms

<table>
<thead>
<tr>
<th>PID</th>
<th>NUM_CUST</th>
<th>C (CNY)</th>
<th>CE</th>
<th>CS</th>
<th>NV</th>
<th>PS_KPSO C (CNY)</th>
<th>CE</th>
<th>CS</th>
<th>NV</th>
</tr>
</thead>
<tbody>
<tr>
<td>C101_25</td>
<td>25</td>
<td>3481.31</td>
<td>19.73</td>
<td>98.4</td>
<td>5</td>
<td>3138.071</td>
<td>19.5642</td>
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**Table 4:** Remaining Test Set Results Comparison

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**Fig. 14:** c201(100) vehicle distribution route

**Fig. 15:** r201(25) vehicle distribution route
Fig. 16: r201(50) vehicle distribution route.

Fig. 17: r201(75) vehicle distribution route

Fig. 18: r201(100) vehicle distribution route

Fig. 19: r211(25) vehicle distribution route

Fig. 20: r211(50) vehicle distribution route

Fig. 21: r211(75) vehicle distribution route
Fig. 22: r211(100) vehicle distribution router

Fig. 23: c201(25) vehicle distribution route

Fig. 24: rc201(50) vehicle distribution route

Fig. 25: rc201(75) vehicle distribution route

Fig. 26: rc201(100) vehicle distribution route

VII. Conclusion

This paper discusses VRPTW along with added constraints of number of vehicles, logistics cost, overall carbon emission rate along with multiple pickup and delivery points. A meta heuristic Ant Colony Algorithm with K-Means Clustering was employed to solve the problem statement. Looking at the literature survey in this paper, it is observable that Vehicle Routing Problem has had several approaches with varying results, which in turn leads to the fact that VRP with added constraints is a difficult problem to solve. The solution provided in this paper has been compared with [32], which has a similar problem statement, and the results of the proposed Ant colony Algorithm with K-Means Clustering has performed far better and has provided very less scope of improvement in the discussed problem areas. The results and findings of this paper pave the way for a better understanding for new solutions and thus will give leverage to go further for more improvement.
References Références Referencias


26. Y. Ma, J. Han, K. Kang, and F. Yan, “An improved aco for the multidepot vehicle routing problem with time windows,” in Proceedings of the Tenth


