Vehicle Routing Problem with Time Window Constrain using KMeans Clustering to Obtain the Closest Customer

By Jai Keerthy Chowlur Revanna & Nushwan Yousif B.Al-Nakash, PhD

Information Systems Engineering and Management & Harrisburg University of Science and Technology

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GJCST-D Classification: F.1.1

VEHICLEROUTINGPROBLEMWITHTIMEWINDOWCONSTRAINUSINGKMEANSCLUSTERINGTOOBTAINTHECLOSESTCUSTOMER

Strictly as per the compliance and regulations of:

Vehicle Routing Problem with Time Window Constrain using KMeans Clustering to Obtain the Closest Customer

Jai Keerthy Chowlur Revanna*, Nushwan Yousif B.Al-Nakash[†], PhD

*Information Systems Engineering and Management

Harrisburg University of Science and Technology

Email: jchowlur@my.harrisburgu.edu, nal-nakash@harrisburgu.edu

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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 in https://www.cogoport.com/blogs/transport-cost (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 spurt 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 Vehicle Routing Problem (VRP), there are initially p vehicles located at a depot that must deliver different amounts of supplies to q customers. Now, the VRP will aim to find the optimal route that a group of vehicles serve a group of users. This way a standard solution is obtained which contains all the routes that start and end at the depot, with the constraint that the goods are delivered within or before the time range set by the customer, capacity limit and the working time of the drivers are also considered.

This paper will discuss how the Ant Colony Optimization with K-Means Clustering (ACO-K-Means) has been employed to minimize costs when delivering goods 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 [1] were the first ones to 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, [2] 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) [3]. Then another solution was introduced by Ichoua et al. [4] 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 research and studies

popped up. Some were utilizing route construction savings method and an insertion method to solve incapacitated TDVRP (time dependent with/without time windows), some had heuristic solutions [8-10], some metaheuristic algorithms [5-7] and others hyper

heuristics [11].Figure 1. shows a generalized view of how a VRP is solved.
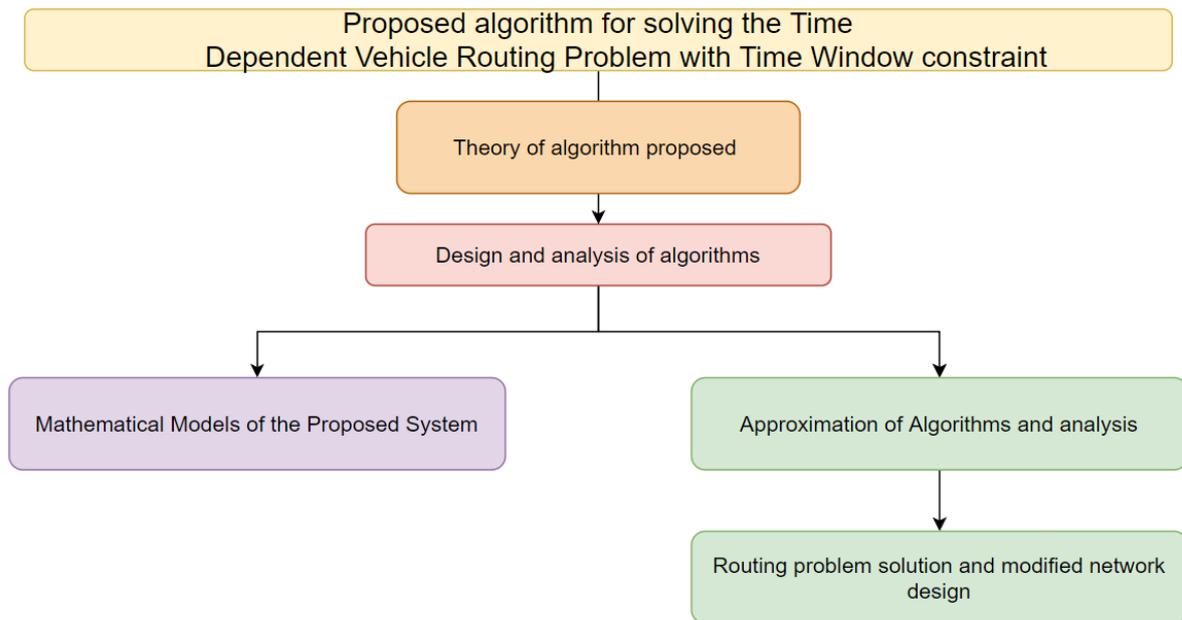
Figure 1: General VRP Solving Method

Many works of solving the VRP with the Time Window Constraint were inherited from the travelling salesman problem. The method used by the salesman to find the best and optimal route to deliver the goods to the respective customers from one or more depot and also take the goods from the customer back to the respective depots within the constraints set, has been extensively used in VRP, with the inclusion of extra constraints. Similar VRP variants have been mentioned below:

- Vehicle Routing Problem with the Time Window Constraint [12] that has been set by customers,
- Another modified VRP with the added constraint of using limited number of vehicles of varying holding capacity has been published as Mixed Fleet Vehicle Routing (MFVRP) [13],
- Another paper which has VRP with an added constraint where customers can request for delivery or pickup with the requirement that in every single delivery route, all pickups and deliveries to the customers are completed. This is known as Vehicle Routing Problem with Backhauls (VRPB) [13].

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, MutsunoriYagiura and ToshihideIbaraki [8]. 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 routes of vehicles 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 used to evaluate the present solution. they even included a filtering method that determines which spaces in the neighbourhood 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 YiyoKuo[6]. In the research paper, the author has considered fuel consumption and carbon 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.

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

Paper [14] 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 improved ant colony optimization (ACO) algorithm with hybridised insertion heuristics and enhanced local search.

Another reference has been taken from [15] 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 idea of disruption management has been employed to create a disruption recovery model with a different type split delivery that is used for inter-route recourse based on a previous TDVRPTW. It takes into account the nature of perishable goods and dynamic travel route choice in urban road networks. The, a tabu search algorithm is brought up to create a solution for the initial routing problem. This will be further extended to create the disruption recovery plan.

[16] Researchers have also used a novel ant colony optimization algorithm based on improved brainstorm optimization (IBSO-ACO) to solve VRP with soft time windows. According to this paper, the classical ant colony algorithm has been modified to efficiently solve the local optimum problem. Their research has given proof that it can achieve a lower routing cost at a high convergence rate than the classical ant colony (ACO) and the stimulated annealing ant colony algorithms.

Looking into other heuristic strategies involved, [17] has the space-filling curve with optimal partitioning

$$\sum_{o \in C_2} \quad p^k{}_{om} - \sum_{y \in C_2} \quad p^k{}_{xn} = 0 \quad \forall k \in K, \forall (m,n) \in R \ (3)$$

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

as a solution while another has three-phase heuristics which has been developed by grouping a heuristic-based clustering algorithm solving VRP [18]. Summary of other important state-of-art modern heuristics is available in [19,20].

In this paper, we will be solving the Vehicle Routing Problem with Time Windows constraint using the modified Ant Colony Optimization 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 [21], which was the first paper to be published on this topic. Papers [22-27] 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 [28]. 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. If there is an order between pickup node m and delivery node, n then there will be a set R which contains pairs of (m,n).

Looking at the objective function that minimizes total travelling cost, equation 1 is as follows

$$min \sum_{k \in K} \quad \sum_{m,n \in C} \quad p^k{}_{mn} r_{mn} \mu_k \qquad (1)$$

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

Equation 2 makes sure that each node is served by at least one vehicle

$$\sum_{k \in K} \quad \sum_{n \in C_1} \quad p^k{}_{mn} \geq 1 \quad \forall m \in C \backslash \{0, x + y + 1\} \quad (2)$$

Equation 3 showcases the constraint where the same vehicle k must pick and order from node m and deliver it to node n.

$$\sum_{n \in C_1} \quad p^k_{0n} \leq 1, \quad \forall k \in K \qquad (4)$$

$$\sum_{n \in C_2} \quad p^k_{n,x+y+1} \leq 1, \quad \forall k \in K \qquad (5)$$

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

$$\sum_{m \in C_2} p_{mn}^k = \sum_{o \in C_2} p_{no}^k \quad \forall n \in C\backslash\{0, x + y + 1\}, k \in K, o \neq m, n \neq m \tag{6}$$

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

$$Tc_m^k + (t_{mn} + s_m) - BigM(1 - p_{mn}^k) \leq Tc_n^k, \quad \forall k \in K, n \in C_1, m \in C_2 \tag{7}$$

$$Lc_m^k + d_n - BigM(1 - p_{mn}^k) \leq Lc_n^k, \quad \forall k \in K, n \in C_1, m \in C_2, m \neq n \tag{8}$$

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

$$Tc_n^k \geq R_{mn}(s_m + t_{mn}) + Tc_m^k, \quad \forall k \in K, m \in P\_S, n \in D\_S \tag{9}$$

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

$$l_m \geq Tc_m^k \geq f_m, \quad \forall m \in C\backslash\{0, x + y + 1\}, k \in K \tag{10}$$

$$(A_k + d_m, A_k) \geq Lc_m^k \geq (0, d_m), \quad \forall k \in K, m \in C \tag{11}$$

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

$$\sum_{k \in K} \sum_{n \in C} p_{0n}^k \leq M \tag{12}$$

$$t_{max} \geq Tc_{x+y+1}^k - Tc_0^k, \quad \forall k \in K \tag{13}$$

This mathematical model is a small-scale solution. Because it being a population based metaheuristic solution, it is to be expanded step by step. Once the pheromone value is successful in small scale, the forging behaviour of ants could be applied to VRP in large scale for large number of vehicles.

IV. APPROACH TO THE SOLUTION

In this paper, the Vehicle Routing Problem with Time Window constraint has been resolved using a modified version of the Ant Colony Optimization using K-Means Clustering. Marco Dorigo was the first person to introduce Ant Colony Optimization, in the 90s, in his Ph.D. thesis. The solution algorithm is based on the behaviour 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. .

Figure 2shows process flow of the proposed solution. The purpose of the optimization model was to reduce specific energy consumption by taking into account the diameter of the pipe, the number of sprinklers, the working pressure of the end sprinklers along the pipeline, and the coordination conditions of the pump pipeline. A pressure drop between adjacent sprinklers has been added to the heuristic function of ACO's design to reflect the distance between the two cities of the Traveling Salesman Problem (TSP).
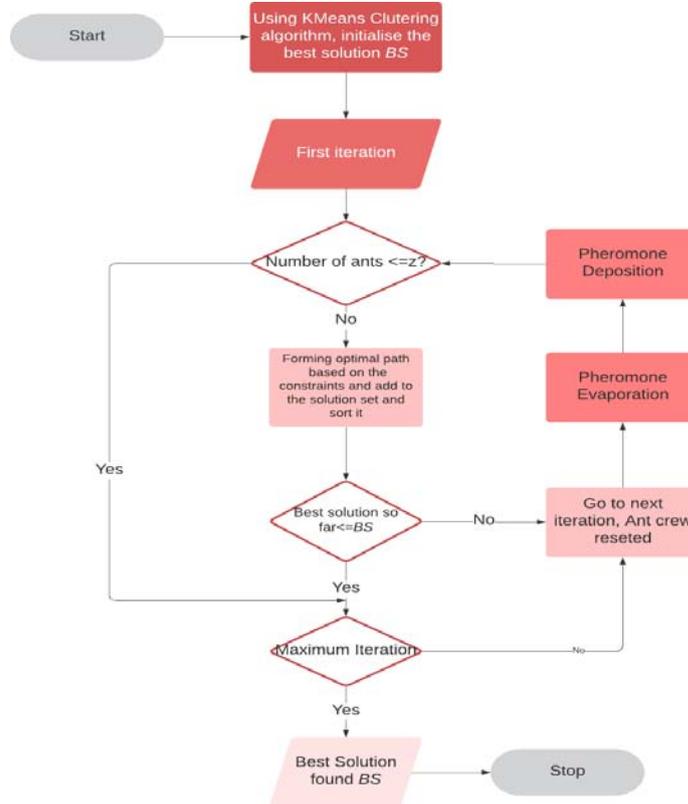
Figure 2: *Process Flow of the Proposed Solution [Reference number]*

As shown in the above figure 2, Ant Colony Optimization (ACO) algorithm is a probabilistic technique based on the above phenomenon to find the optimal 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 wherein a pickup point might or might not have multiple delivery locations.

a) *Parameter initialization*

Looking at the research done in [28], 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 τ_{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 kth ant will use the pheromone trail τ_{mn} which is showcased below in equation 14:

Initially, all probabilities are set to 1. $\lambda = \frac{1}{r_{mn}}$ is a heuristic value, pheromone concentration on the edge when the ant travels from node m to node v_n is denoted by τ_{mn} and relative influence of the pheromone concentration and the heuristic value is shown by α and β.

If we go into the specifics, then λ_{mn} denotes how much favourable is the next node n while τ_{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 limit of route length has been reached or when the time window constraint has been disobeyed. so, in forming the route, the ant will check each node whether it fulfils all the constraints and if it finds 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 a solution set, which will then be used for finding the best solution $\square\square$ 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 Where trail persistence $1 \geq \rho \geq 0$ of the evaporation factor $1 \geq \left(\frac{\theta}{S_{avg}} + \rho\right) \geq 0$ and θ is a constant. In each iteration, z number of ants find

decrease those that are on bad solution paths. In pheromone deposition and evaporation, pheromone values either increase or decrease at a constant rate [29].

The pheromone evaporation equation is given as such,

$$\tau_{mn} = \tau_{mn}\left(\frac{\theta}{S_{avg}} + \rho\right), \qquad \forall(m,n) \in A \qquad (15)$$

$S_{avg} = \sum_{k=1}^{z} \frac{S^k}{z}$ of average total distance. Then pheromone is updated by the elitist and best ants

After the evaporation process, only the best and the elitist ants can update the pheromone deposits on the optimal path chosen, which is given by the equation

$$\tau_{mn} = \tau_{mn} + \Delta\tau_{mn}^* + \sum_{b=1}^{\sigma-1} \tau_{mn}^b \qquad (16)$$

Where,(16)

$$\Delta\tau_{mn}^\lambda = \{\frac{\sigma-}{S^\lambda} \qquad if\ \lambda th\ best\ ant\ travels\ on\ edge\ (m,n)0\ 0 \qquad otherwise \qquad (17)$$

$$\Delta\tau_{mn}^* = \{\frac{\sigma}{BS} \qquad if\ best\ part\ of\ solution\ is\ (m,n)0 \qquad otherwise \qquad (18)$$

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 σ elitist ants have travelled a path, that path will be updated as the best solution so far (BS), in accordance with the ACO+K-Means 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 traversed. The term $\Delta\tau_{mn}^\lambda$ 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^λ and rank λ and the value is equal to $\Delta\tau_{mn}^\lambda$. 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 [17] so as to reduce pheromone deposition on those routes that have relatively lesser favourability.

V. 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 [30] 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 [30] as this paper is in comparison with the latter. Similar to [30] the delivery vehicle used is a refrigerator car and the set of pre-defined parameters as shown in table 1 given below.

Table 1: Parameters to Be Used Throughout this Paper

Parameters	Implications	Predefined Value
g	Gravitational constant of Earth	$9.81\ kg/m^2$
P	Density of atmosphere	$1.225\ kg/m^3$
θ	Gradient	0
ΔT	Temperature Difference between container of vehicle and atmosphere	$20°C$
λ	Frequency of opening the vehicle door	0.6
t_c	Transportation price of per unit weight of goods	1
δ	Decline coefficient of product freshness	0.01
ε_1	Early arrival time penalty coefficient	0.6
ε_2	Late arrival time penalty coefficient	0.8
R_n	Number of iterations of pheromone renewal	20
α	Weight of pheromone concentration	1
β	Weight of heuristic function	3
ρ	Volatility coefficient	0.8
q^f	The parameter of the selection rule of Pseudo-random proportional action	0.9
τ_{min}	Minimum value of pheromone	0.001
τ_{max}	Maximum value of pheromone	10
w_1, w_2, w_3	Weights of optimization objectives	$\frac{1}{3}$
R	Fuel consumption per unit time $(\frac{g}{s})$	22.37
h	Fuel consumption and carbon emission conversion factor $(\frac{L}{kg})$	1/2.7
δ	Fuel-air ratio	1
φ	Engine friction factor	0.2
T	Engine speed of refrigerated truck(r/min)	2000
V_s	Air Displacement(L)	1.051
η	Effective power transmission	0.45
μ	Energy consumption constant	44
M_q	Refrigerated truck weight(kg)	1510
A	Windward area of vehicle(m²)	3.96
C_d	Coefficient traction	0.4
C_r	Coefficient of rolling resistance	0.01
γ	Heat transfer coefficient refrigerated truck	0.4
S_w	External surface area of refrigerated truck(m²)	43.36
S_v	Interior surface area of refrigerated truck(m²)	22.32
	Vehicle maximum load	200
	Vehicle fixed cost	200
	Soft time window	20
	Carbon tax	20

c) Result Analysis

The entire result section has used the Pareto optimal principle for obtaining the solution. The Pareto Principle states that 80 percent of a project's benefit comes from 20 percent 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 id obtained. Referring to [30], this paper the objectives chosen will be carbon emission reduction, total cost, time frame and customer satisfaction.

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 from figure 3 to figure 26.

Table 2: Shows the Legends used in this Paper

CNY	Cost in CNY
CE	Carbon Emissions
CS	Customer Satisfaction
NY	Number of Vehicles Used

Table 2 shows the used legends as explained in figure 3, figure 5, figure 7 and figure 9.

i. *25 Customers*

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 [3] and this paper. It is clearly visible from the graph that the proposed algorithm of ACO+K-Means [PS_KPSO] clustering has better output in terms of carbon emission, customer satisfaction and total transportation cost. ACO (Ant Colony optimization) and ACOMO (Ant Colony optimization Multi objective) which is heuristic function.
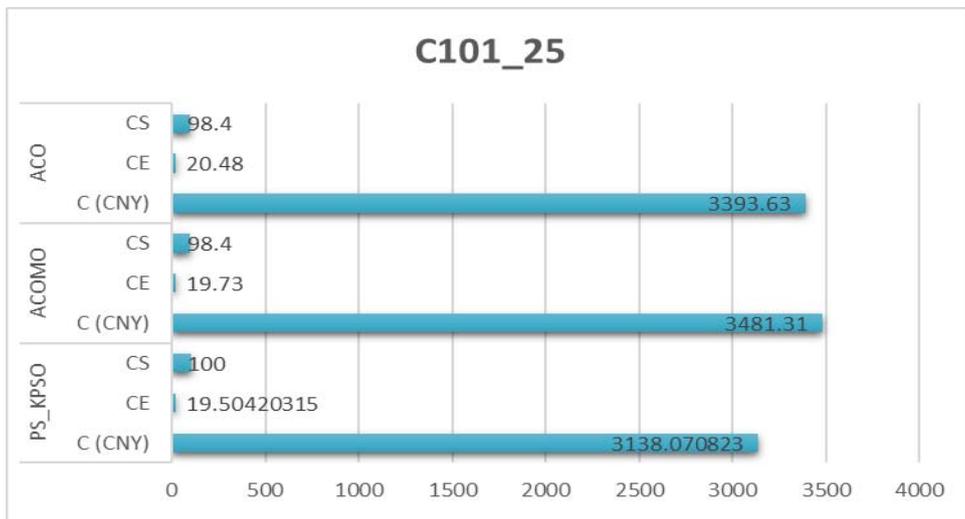
Figure 3: c101(25) comparison with [30] (ACOMO) and ACO+K-Means Clustering (PS_KPSO)

PS_KPSO algorithm has given total cost as 3138.07, lower carbon emission of 19.50 and 100 percent customer satisfaction in all cases. Below in figure 4, showst he 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)

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, 50, 49, 47,0), (0, 5, 3, 7, 8, 10, 11, 9, 6, 4, 2, 1,0), (0, 20, 24, 25, 27, 29, 30, 28, 26, 23, 22, 21,0), (0, 32, 33, 31, 35, 37, 38, 39, 36, 34,0) and (0, 13, 17, 18, 19, 15, 16, 14, 12, 0). The end results are 33.43 for carbon emissions, 5942.72 cost and 100 percent customer satisfaction. Figure 5 shows the comparison between [30] and this paper results while figure 6 displays the routes taken by the 5 trucks.


Figure 4: c101(25) vehicle distribution route50 Customers
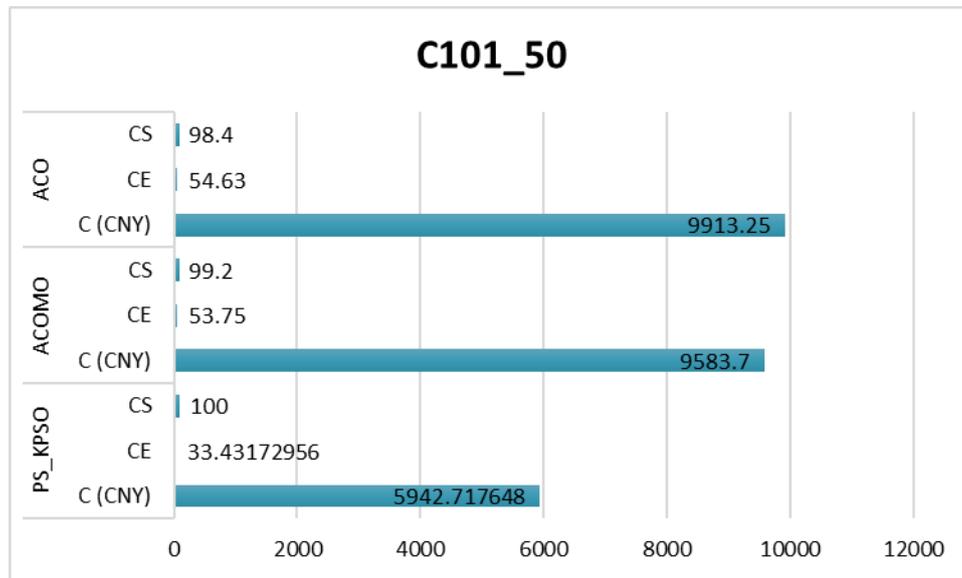
Figure 5: *c101(50) comparison with [30] (ACOMO) and ACO+K-Means Clustering (PS_KPSO)*
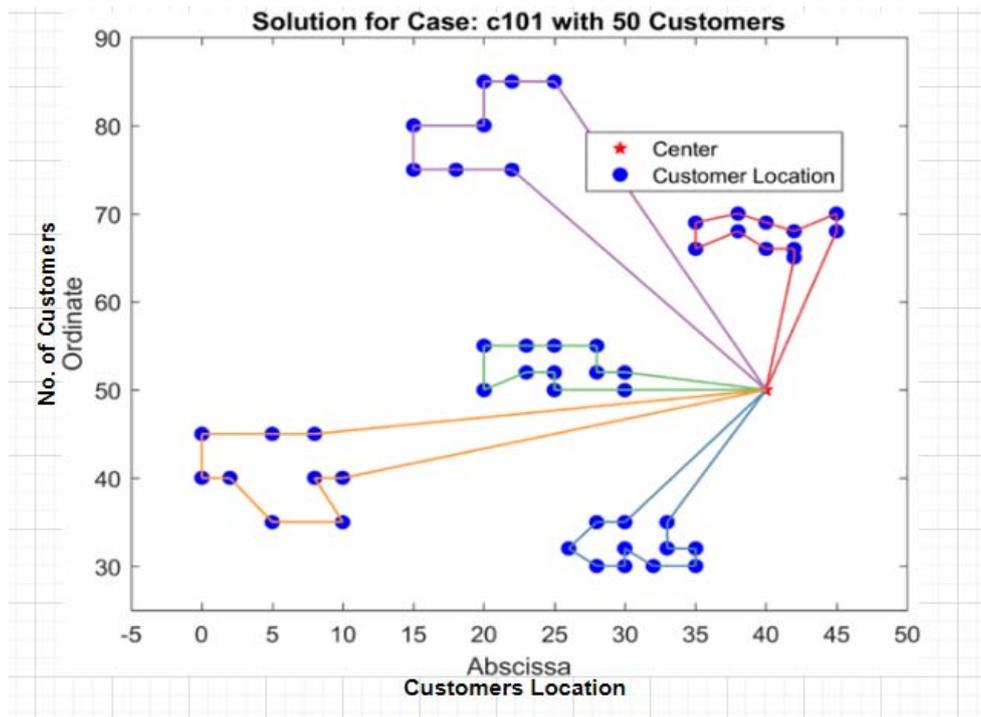
Figure 6: *c101(50) vehicle distribution route*

ii. *75 Customers*

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, 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 [30] and this paper and the route distribution of the vehicles
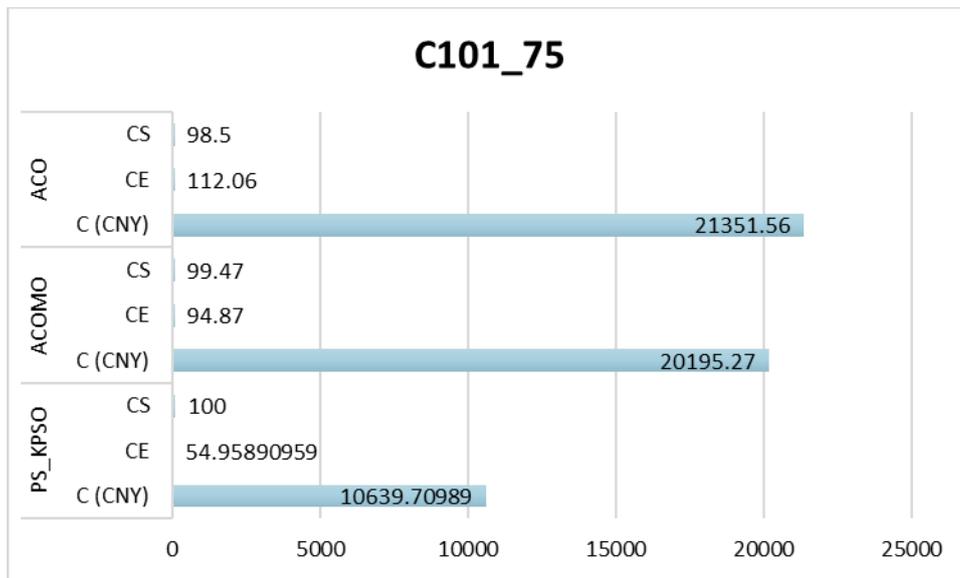
Figure 7: c101(75) comparison with [30] (ACOMO) and ACO+K-Means Clustering (PS_KPSO)
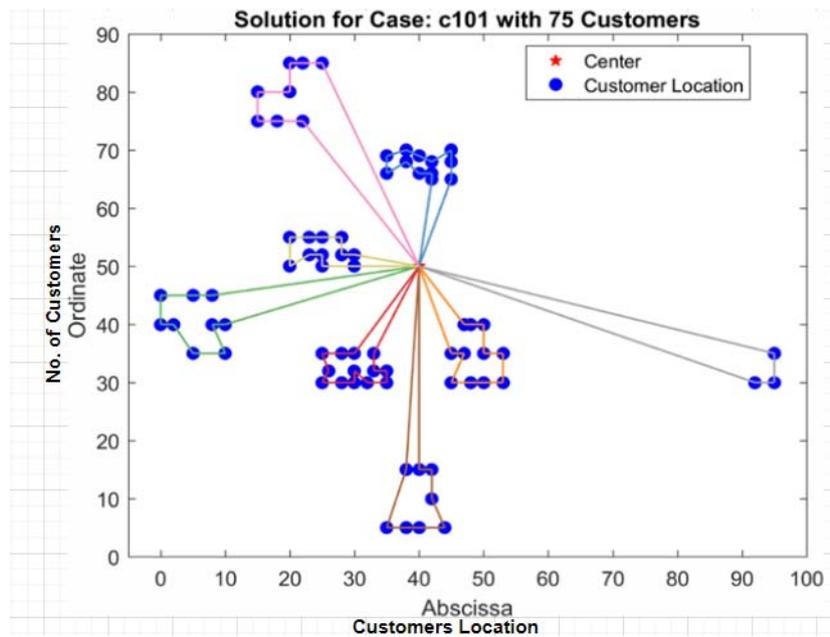
Figure 8: c101(75) vehicle distribution route

iii. *100 Customers*

This section has used the c101 (100) dataset. Now looking [30], 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 vehicles have been employed and the most optimal paths are chosen: (0, 5, 3, 7, 8, 10, 11, 9, 6, 4, 2, 1, 75, 0), (0, 43, 42, 41, 40, 44, 46, 45, 48, 51, 50, 52, 49, 47, 0), (0, 20, 24, 25, 27, 29, 30, 28, 26, 23, 22, 21, 0), (0, 67, 65, 63, 62, 74, 72, 61, 64, 68, 66, 69, 0), (0, 90, 87, 86, 83, 82, 84, 85, 88, 89, 91, 0), (0, 57, 55, 54, 53, 56, 58, 60, 59, 0), (0, 98, 96, 95, 94, 92, 93, 97, 100, 99, 0), (0, 32, 33, 31, 35, 37, 38, 39, 36, 34, 0), (0, 13, 17, 18, 19, 15, 16, 14, 12, 0), (0, 81, 78, 76, 71, 70, 73, 77, 79, 80, 0). Figures 9 and 10 showcase the comparison between [30] and this paper and the route distribution of the vehicles.
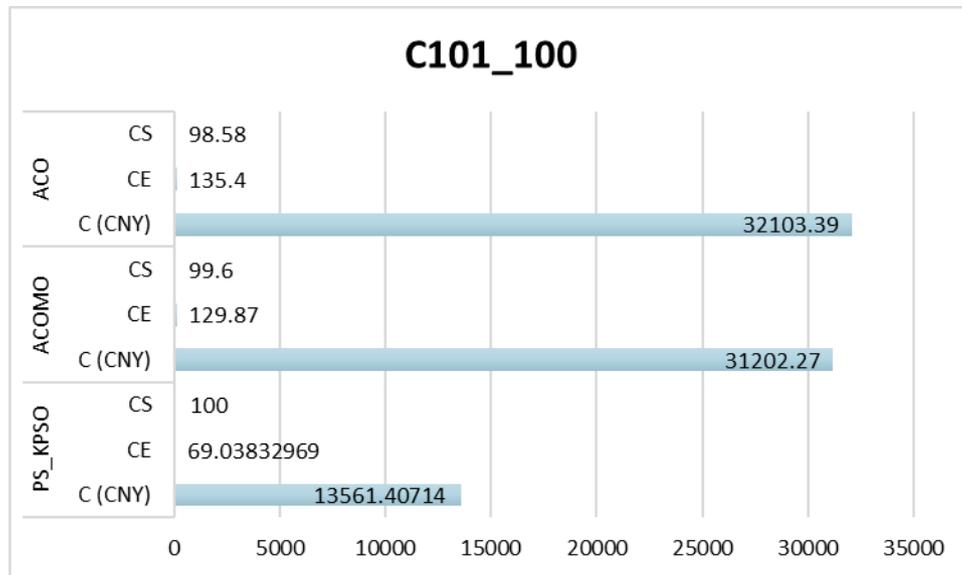
Figure 9: c101(100) comparison with [30] (ACOMO) and ACO+K-Means Clustering (PS_KPSO)
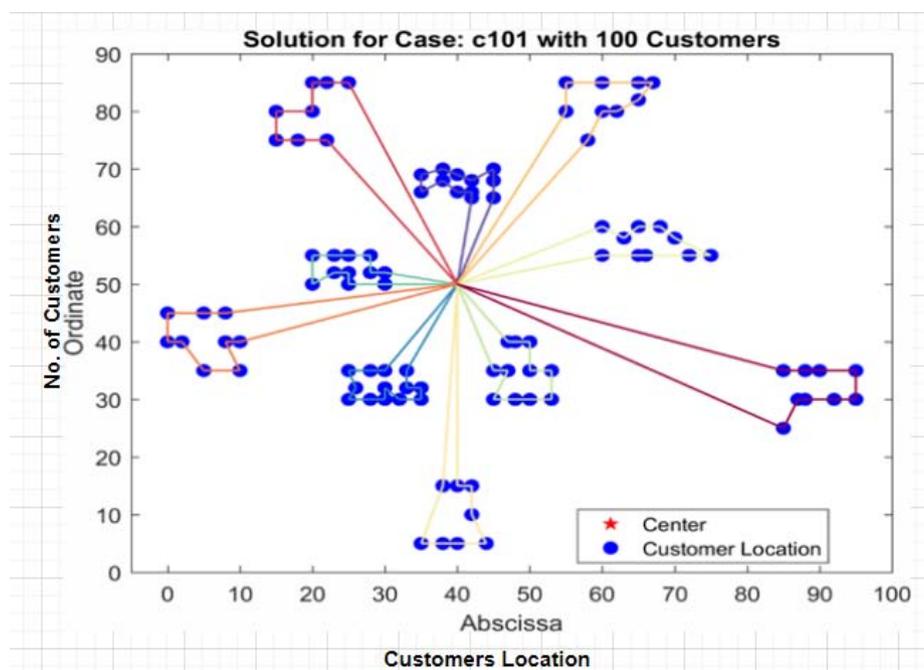
Figure 10: c101(100) vehicle distribution route

d) Comparison

Looking at all the results above, it is easily discernible that the ACO+K-Means clustering algorithm has performed way better than the improved Ant Colony algorithm and the normal Ant Colony Algorithm. With lesser number of vehicles employed, lesser carbon emission levels noted and better cost management, the proposed system has shown its effectiveness and viability for usage in the 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 while there are about 46.61% , 53.27% and 61.16% reduction in total carbon emissions for 50, 75 and 100 customers, when compared with [30]. Along with the aforementioned improvements, there is 100% customer satisfaction in all the cases. The proposed algorithm (ACO+K-Means Clustering) has outperformed the Modified Ant Colony Algorithm and the original Ant Colony algorithm. Table 3show results compared with Table of that obtained by the proposed algorithm and modified ant colony algorithm.

Table 3: Comparison between algorithms [30]

PID	NUM_CUST	ACOMO				PS_KPSO			
		C (CNY)	CE	CS	NV	C (CNY)	CE	CS	NV
C101_25	25	3481.31	19.73	98.4	5	3138.070823	19.50420315	100	3
C101_50	50	9583.7	53.75	99.2	11	5942.717648	33.43172956	100	5
C101_75	75	20195.27	94.87	99.47	17	10639.70989	54.95890959	100	8
C101_100	100	31202.27	129.87	99.6	23	13561.40714	69.03832969	100	10

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+K-Means algorithm) and modified Ant Colony algorithm [30] have been given in Table 4.

Table 4: Remaining test set results comparison

PID	NUM_CUST	TOT_VEH	PS_KACO				ACOMO		
			NV	C	CE	CS	NV	C	CE	CS
C_201_25	25	25	2	215.543	14.864	100	3	613.81	22.28	100
C_201_50	50	25	2	444.961	19.7345	100	6	1232.8	42.46	100
C_201_75	75	25	3	511.09	26.2824	100	9	2177.34	58.81	100
C_201_100	100	25	3	591.557	27.9907	100	13	2221.71	99.08	100
r_201_25	25	25	2	543.693	21.8306	100	5	946.39	45.17	100
r_201_50	50	25	2	1039.39	32.3543	100	6	1404.82	69.75	100
r_201_75	75	25	3	1368.58	44.4869	100	7	2482.75	98.4	100
r_201_100	100	25	4	1995.19	62.9339	100	13	2931.63	111.02	100
r_211_25	25	25	1	375.432	13.1144	100	2	400	24.11	100
r_211_50	50	25	2	1391.42	39.8279	100	7	600	44.87	100
r_211_75	75	25	2	1199.99	35.7638	100	7	873.41	72.94	100
r_211_100	100	25	3	1867.28	55.0745	100	9	1080.64	84.49	100
r_c201_25	25	25	2	454.046	19.9274	100	4	847.18	31.43	100
r_c201_50	50	25	3	974.703	36.1249	100	8	1554.47	80	100
r_c201_75	75	25	4	1623.5	55.0429	100	10	2186.5	121.39	100
r_c201_100	100	25	4	1927.47	61.4963	100	11	2959.41	139.2	100

The data from Table 4 helps in evaluating the effectiveness 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 number of customers. As the number of vehicles employed is less, 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.

f) Terms

The below terms explain the pareto optimal solution which are explained from figure 3 to figure 24. It explains the co-efficient used in capacity of the vehicles and number of customers.

C101(25)- Cost efficient Pareto optimal solution set and its multidimension interpolation for 25 customers

C101(50)- Cost efficient Pareto optimal solution set and its multidimension interpolation for 50 customers) Cost efficient Pareto optimal solution set and its multidimension interpolation for 75 customers

R101(25)- Fuel Co efficient solution set and its multidimension interpolation for 25 customers

R101(50)- Fuel Co efficient solution set and its multidimension interpolation for 55 customers

R101(75)- Fuel Co efficient solution set and its multidimension interpolation for 75 customers

RC101(25)- Fuel and cost Co efficient solution set and its multidimension interpolation for 25 customers

RC101(50)- Fuel and cost Co efficient solution set and its multidimension interpolation for 50 customers

RC101(75)- Fuel and cost Co efficient solution set and its multidimension interpolation for 75 customers

The Figueres 11 to figure 24 shows case 1 and case 2 shows optimal path, cost and fuel efficiency. shows the obtained Pareto optimal solution and its multidimensional linear interpolation by using the c101 (25) to c(101)100 customers test table for the above table 4.
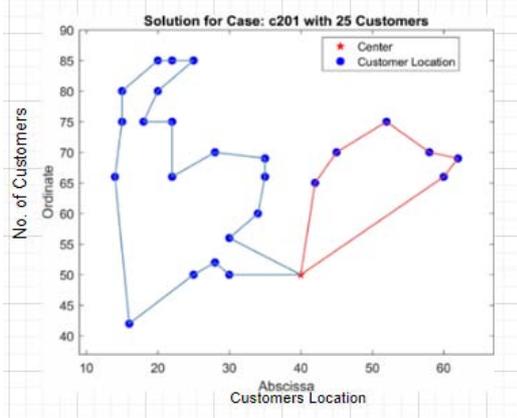
Figure 11: c201(25) vehicle distribution route
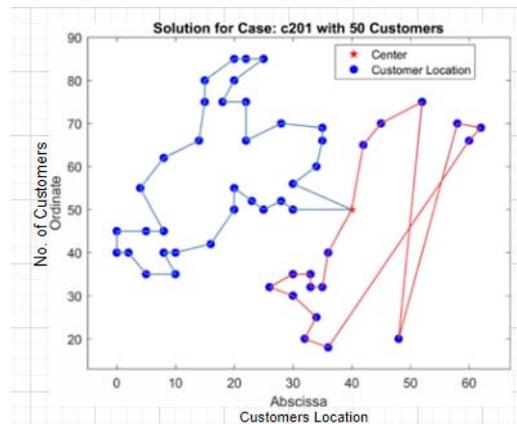
Figure 12.: c201(50) vehicle distribution route
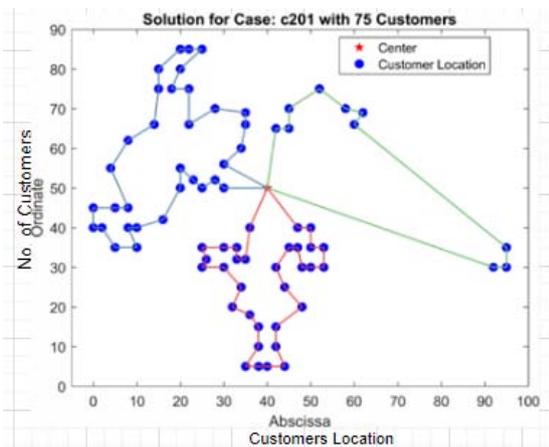
Figure 13.: c201(75) vehicle distribution route
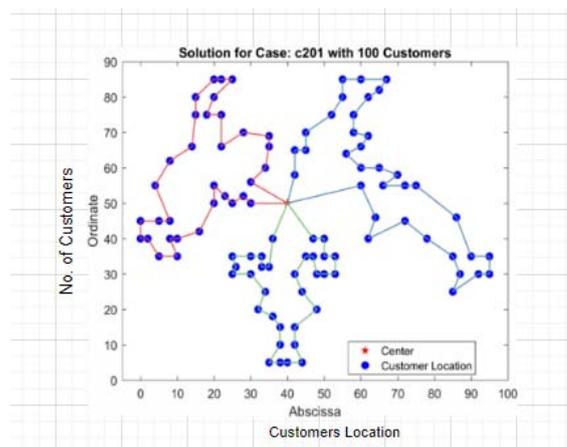
Figure 14.: c201(100) vehicle distribution route
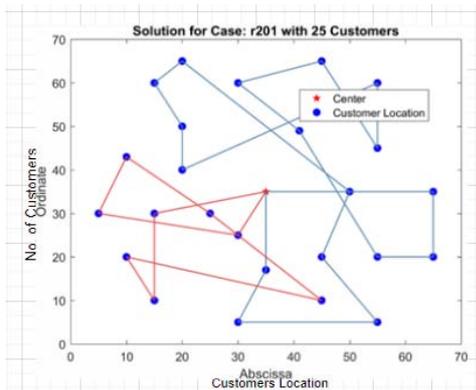
Figure 15.: r201(25) vehicle distribution route
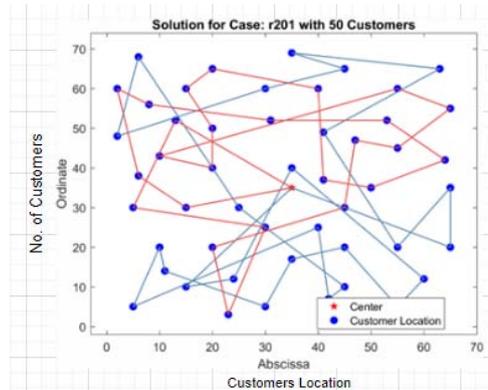
Figure 16.: r201(50) vehicle distribution route
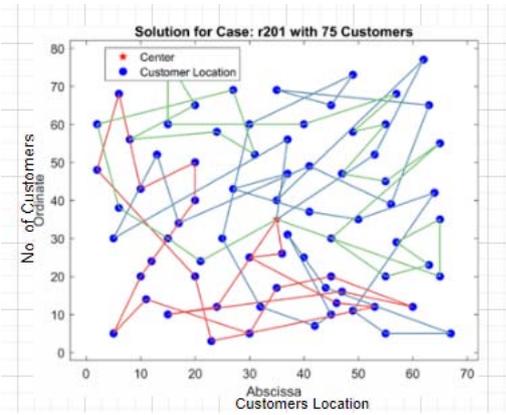
Figure 17.: r201(75) vehicle distribution route
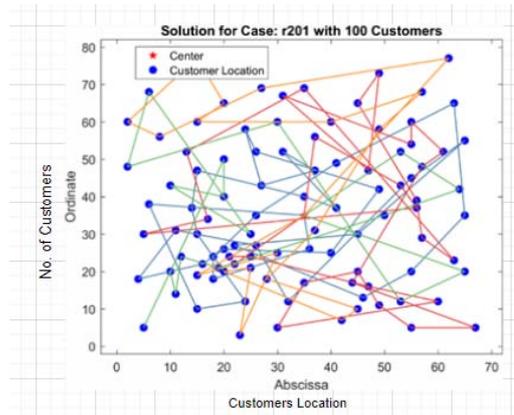
Figure 18.: r201(100) vehicle distribution route
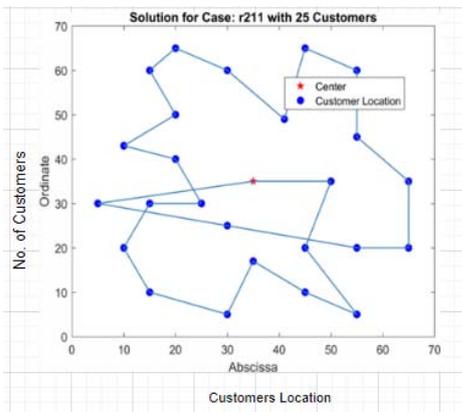
Figure 19.: r211(25) vehicle distribution route
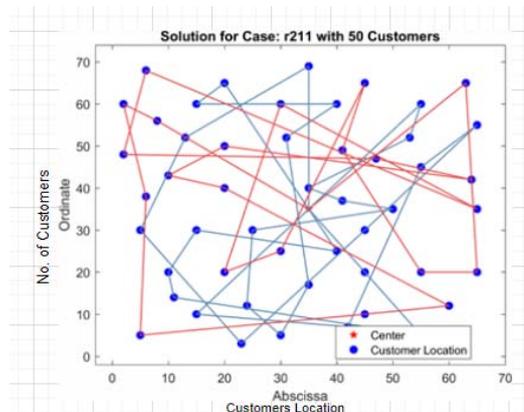
Figure 20.: r211(50) vehicle distribution route
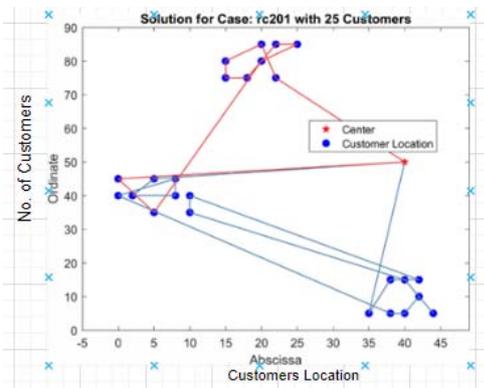

Figure 21.: rc201(25) vehicle distribution route
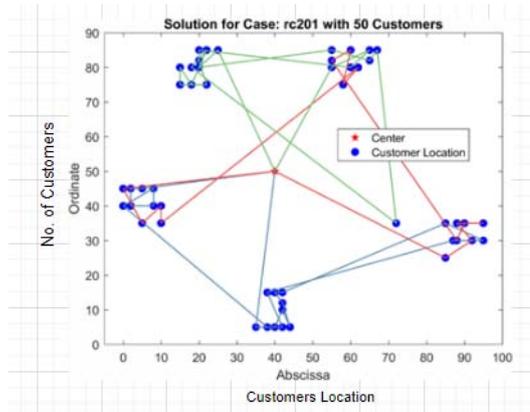
Figure 22.: rc201(50) vehicle distribution route
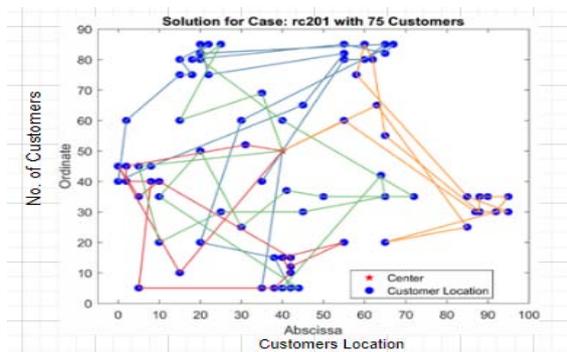
Figure 23.: rc201(75) vehicle distribution route
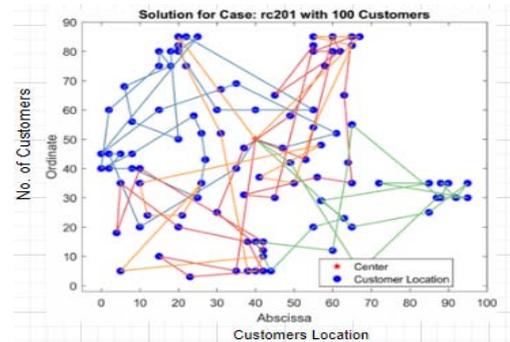
Figure 24.: rc201(100) vehicle distribution route

ptimal solutions in the figure. The number of optimal solutions is less than the one with the test set having 25 to 100 customers. Generally, the fewer the optimal solutions ther are, the fewer distribution plans the distribution center can choose. As an important factor in cold chain logistics, temperature control plays an active role in cold chain logistics distribution. The strict

temperature control can effectively reduce the impact of temperature fluctuations on cargo in cold chain transportation. To a certain extent, refrigeration equipment has caused an increase in carbon emission. Below table 5 explains from optimal path, fuel, and cost efficiency for above figure 11 to figure 24

Table 5: Vehicle distribution route for optimal path, fuel, and cost efficiency

Figure Number	Comments
Figure 11.: c201(25) vehicle distribution route	The Figure 11 shows vehicle distribution for case 2, it shows optimal path for 25 customers
Figure 12.: c201(50) vehicle distribution route	The Figure 12 shows vehicle distribution for case 2, it shows optimal path for 50 customers
Figure 13.: c201(75) vehicle distribution route	The Figure 13 shows vehicle distribution for case 2, it shows optimal path for 75 customers
Figure 14.: c201(100) vehicle distribution route	The Figure 14 shows vehicle distribution for case 2, it shows optimal path for 100 customers
Figure 15.: r201(25) vehicle distribution route	The Figure 15 shows vehicle distribution for case 2, it shows fuel efficiency for 25 customers
Figure 16.: r201(50) vehicle distribution route	The Figure 16 shows vehicle distribution for case 2, it shows fuel efficiency for 50 customers.
Figure 17.: r201(75) vehicle distribution route	The Figure 17 shows vehicle distribution for case 2, it shows fuel efficiency for 75 customers.
Figure 18.: r201(100) vehicle distribution route	The Figure 18 shows vehicle distribution for case 2, it shows fuel efficiency for 100 customers.
Figure 19.: r211(25) vehicle distribution route	The Figure 19 shows vehicle distribution for case 2, it shows fuel efficiency for 25 customers for random vehicles.
Figure 20.: r211(50) vehicle distribution route	The Figure 20 shows vehicle distribution for case 2, it shows fuel efficiency for 50 customers for random vehicles.
Figure 21.: rc201(25) vehicle distribution route	The Figure 21 shows vehicle distribution for case 2, it shows fuel and cost efficiency for 25 customers for random vehicles.
Figure 22.: rc201(50) vehicle distribution route	The Figure 22 shows vehicle distribution for case 2, it shows fuel and cost efficiency for 50 customers for random vehicles.
Figure 23.: rc201(75) vehicle distribution route	Figure 23 shows vehicle distribution for case 2, it shows fuel and cost efficiency for 75 customers for random vehicles.
Figure 24.: rc201(100) vehicle distribution route	The Figure 24 shows vehicle distribution for case 2, it shows fuel and cost efficiency for 100 customers for random vehicles.

VI. Conclusion

This paper discusses the vehicle routing problem with time window constraint (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 [30], which has a similar problem statement, and the results of the proposed ant colony algorithm with K-Meansclustering has performed far better and has provided very less scope of improvement in the discussed problem areas.

In future research on similar topics, it's a hope that this paper will be a good leverage for the researchers and this solution can be further modified for more improvements.

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