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Route optimization via improved ant colony algorithm with graph network

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ABSTRACT

Route optimization problem using vehicle routing problem (VRP) and time window constraint is explained as finding paths for a finite count of vehicles to provide service to a huge number of customers and hence, optimizing the path in a given duration of the time window. The vehicles in the loop have restricted intake of capacity. This path initiates from the depot, delivers the goods, and stops at the depot. Each customer is to serve exactly once. If the arrival of the vehicle is before the time window "opens" or when the time window "closes," there will be waiting for cost and late cost. The challenge involved over here is to scheduling visits to customers who are only available during specific time windows. Ant colony optimization (ACO) algorithm is a meta-heuristic algorithm stimulated by the growing behaviour of real ants. In this paper, we combine the ACO algorithm with graph network henceforth increasing the number of vehicles in a particular depot for increasing the efficiency for timely delivery of the goods in a particular time width. This problem is solved by, an efficient technique known as the ACO+graph algorithm.

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1. INTRODUCTION

Vehicle routing problem with time windows (VRPTW) has been a basic issue to transport goods that are to be delivered within a time bandwidth is a trending topic for research in the upcoming years. This task is elaborated as selecting routes for restricted number of vehicles to serve a group of customers in the allotted time window. The vehicle has a specific capacity. It initially begins from the depot and ends at the depot. All the customers are to be served exactly once. The main objective of the proposed system is to reduce the total transport costs. This paper presents a transportation system for graph database to process the required information. The databases used here demand information collected from all sources like vehicle maps, and timetable, the path traversed from source to destination to incorporate the features to find an optimal path, which will handle many users, to achieve efficiency to scale the system. Relationship between the objects to integrate the primary constraints where a transport stops. To achieve efficiency to select a particular algorithm in the form of a computer memory. Graph databases are chosen based on the concept of structured query language (SQL). The possibility of storing a graph in a graph based system. To determine the efficiency and scalability to use data integrity along with accessibility.

As a result, an evolutionary algorithm (EA) is presented to handle optimization difficulties [1], hence enhancing efficiency. Particle swarm optimization (PSO) is one of these techniques that has proven to be effective in solving a variety of challenging optimization problems. We describe an improved ant system approach for the vehicle routing problem (VRP) with a single central depot and several similar vehicles in this work. The goal is to solve combinatorial optimization issues by mimicking the behavior of ant colonies based on observations of real ants hunting for food. Real ants have been discovered to use a fragrant essence called pheromone to relay information about food sources. The behavioral mechanism described above can be used to solve combinatorial optimization problems by simulation.

Wang *et al*. [2] offer an improved ant system solution for the VRP by increasing the total number of vehicles for timely product delivery, and show that the ant pattern for food finding may be employed to provide competitive outcomes. Cluster analysis is a type of mathematical analysis method encountered, as well as a type of machine learning method without supervisor monitoring that belongs to NP difficult problems [3], but the analysis method over here has been widely applied in image identification, information retrieval, data mining, statistics, machine learning, spatial database [4], and bifurcation analysis. ACO has improved the results of a series of combinatorial optimization solutions, and by applying ACO to practical problems, Braekers *et al*. [5] researchers have proposed the artificial ant colony concept; artificial ant colony and real ant colony have many similarities, but artificial ant colony has unique skills that real ant colony lacks. In the section, based on introducing ACO thought, it designs the algorithm prototype system, provides optimization, and improves the opinions for the system. The goal of VRPTW [6]-[8] is to choose the best vehicle route from a set of possible options. The goal is to keep the whole cost as low as possible. The dimension's encoding approach is used for the VRPTW with demand points in this paper due to the unknown number of cars. Two dimensions are involved for each demand point. The serial number of the vehicle that serviced the demand point is the first point. The serial of the serviced demand point is the second point. Each particle conveniently correlates to a matrix in which the first dimension corresponds to the serial number of vehicles and the second dimension corresponds to the serial number of consumers.

They propose that a multiswarm cooperative particle swarm optimizer (MCPSO), which is a variant of the PSO form [9]. It employs a multiswarm cooperative evolutionary method in which the master swarms alter their particles based on their own knowledge and that of the slave swarms' particles, while the slave swarms carry out PSO separately to obtain particle diversity. In the context of faster route generation by implementing artificial intelligence (AI) technique onto it, implemented on an intelligent system to estimate the consumption of energy and estimate the travel time by application of heuristics algorithms to solve vehicle routing problems. An efficient meta-heuristic technique selected to be applied on this generalization for vehicle routing problem to achieve better performance. A theoretical approach is carried out which states that a generic approach is used to combine different techniques to solve this problem [10]. The technique is based on re-optimizing or re-routing approach. This approach is tested with seven different techniques and the results are obtained based on the heuristic approach. This also involves by minimizing the no of customers for service. The feasibility of the solution approach decreases for path optimization by reducing the number of vehicles. The infeasibility problem occurs while there will the customer no longer serviced in a specific time window. A deep learning based automatic vehicle location system (AVLS) system-modelling technique is proposed to develop vehicle routes in this system [11]-[14]. An optimization-based approach is significantly using deep reinforcement learning strategy to estimate the parameters of the model. This approach is sensitive to many parameters like time, which is quite time consuming. A neural network-based optimization strategy is developed for vehicle routing in minimum computation time. Figure 1 shows the sample representation of a graph network. Consider a road network below consists of vertices and arcs. Vertices are depots, intersections, and customers, arcs are roads, which are directed or undirected [15].

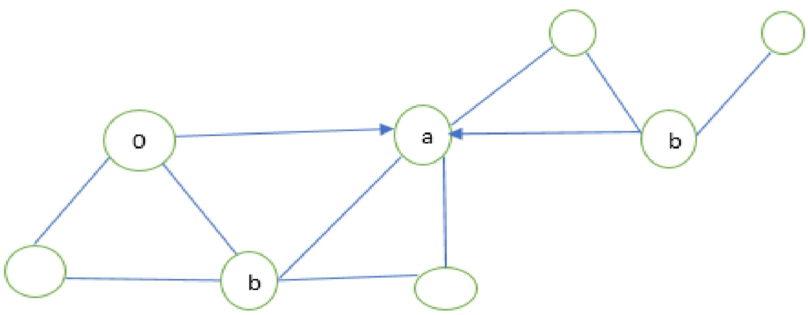

Figure 1. Sample representation of a graph network

2. RELATED WORK

The multi-compartment electric vehicle routing problem (EVRP) with a soft time window and multiple charging kinds is discussed here [16], [17] where electric multi-compartment cars are used that are environmentally benign but require charging during the transportation process. The goal of this optimization issue is to minimize the function composed of vehicle cost, distribution cost, time window penalty cost, and billing service cost using a mathematical model. An estimation of the distribution algorithm based on Lévy flight (EDA-LF) is presented to overcome this problem by doing a local search at each iteration to avoid the algorithm from falling into a local optimum [18]. The EDA-LF method finds better solutions and is more robust than the basic EDA algorithm, according to experimental results. A graph data model consists of data structures [19], different constraints while implementing a task to perform connections in transport environment. These databases refer to the category of NoSQL databases. They have high efficiency and handle many users, while using a graph database to enhance the quality of the system to shorten the response time and simply implement different functions. The vehicle routing problem along with time window constraints along with road-network information [20]. At first, a customer-based graph is introduced to solve the problem of specificity. The vehicle routes are defined for customer-based graphs, a dynamic approach is considered for to estimate the travel-time with minimum cost and derive optimal solutions for the problem. Vehicle routing problems are solved by customer graphs where many attributes are embedded in road segments, alternate paths are considered on different customer graphs [21], [22]. Two methods are used to handle customer-based graphs to represent different attributes defined in road segments.

To represent multigraph road networks where an arc is introduced for each path, an exact solution is developed to determine the paths, which are not dominated by linking a set of points interested in a road network. The proposed algorithm used here is multi-dimension multi-objective searching strategy. The efficiency to solve a road network problem to reduce the cost. The optimal solution to the road network to find instances, which are not feasible to use the shortest path, which is carried to in the form of simple representation [23]. Significant research is carried out to solve problems related to VRP to accomplish the objectives to reduce the total cost, total distance, the solutions for VRP are classified into three types exact methods, heuristics and meta heuristics, the exact methods are further classified into branch and X, constant programming and dynamic programming. VRP problems are said to be NP-hard, solving these problems is time-consuming. The customer-based graph for time dependent VRPTW to build two algorithms with road network for multigraphs. Several vehicle routing problems to compute customer-based graph network. The main goal here is to emphasize on tackling large class of vehicle routing problem. The possible enhancement for recent advancement in technology to obtain the real-time traffic condition scenario [24], [25]. A graph database is implemented to find an optimal solution while connecting two stops in vehicle routing scenario. Graph databases are categorized using segmentation known as non-relational database known as NoSQL database. A graph model is constructed for transportation problem for vehicle routing in task orientation to traverse an optimal search path. The path-shift from public transport system to classic modelling of the graph technique has been exploited to transform between different relations of a database. A detailed representation of public transportation system is carried out and a relational graph-based model is developed [26].

Edge computing, traffic management are studied in detail in the transportation of green vehicle systems. There are different mechanisms for different state-of-art approaches to attain the necessary energy efficiency for various green vehicle systems [27]. Offloading circumstances, in edge computation for outsourcing the requirements by predicting the estimated arrival of different workloads, employing AI technique to facilitate between switching the harvesting states from one state to another. In 6G era, numerous vehicles are connected using the same infrastructure providing secure communication for vehicle routing for different problems. The unauthorized users pose a security threat to different vehicle owners by intruding the system while accessing the system resources. The similarities between VRP and JSPs problem are studied, they have the same scenario in execution of their tasks, and their resources are constrained based on the capacity to process their number of tasks. Here exists a time interval that depends on the consecutive execution of tasks to minimize the various lengths of the windows to be executed while specifying a new relationship altogether as far as the capacity constraints are considered [28]. An optimizing the criteria for minimizing various definitions to compress the length of activities to minimize each transition time. A similar technology is used for scheduling as well as vehicle routing problems.

The customer-based graphs representing a road network, to analyze different graph routing problems to achieve alternate paths to handle different limits [28]. The efficiency to tackle the problem on the road network is compared along the multigraph approach. They have developed a multigraph approach for branch-and-price algorithm to improvise the solution of to conduct and analyze the characteristics of VRPTW, which effect the performance with road network and multigraph settings. First step is to develop an algorithm to estimate the associated shortest paths based on the road network to find the instances of expected departure time. To adapt a road network which is based on time-dependent algorithm. The optimal solution found for the road network for different instances, which are not feasible to use the shortest path for the representation.

Friggstad [11] a VRPTW plays a key role in all business operations, recently this has allowed the operations to be carried out in a real time scenario. Latest technologies also possess new problems to the business management techniques, which affects the decision-making approach for dynamic VRPTW problems as well. A generic approach is proposed here to solve this problem, this algorithm serves as a basis for other new algorithms like the insertion approach and DVRPTW, as well as MACS, and these algorithms were compared with many state-of-art-techniques, the best performing algorithm is selected in comparison with other literature review techniques [29]. Meta–heuristics technique requires more CPU time, and are very complex for implementation purposes. The real-life applications choose flexible approach, to cluster these practical applications; few methods are more attractive and effective for tackling complex constraints. The solution approach for local meta-heuristic techniques improves the complex constraints involved in it. The ACO approach is implemented by considering the analogy of real ant colonies for food [30].

3. PROPOSED METHOD

The optimization according to the path by considering three parameters: i) a depot where many customers are serviced, ii) many vehicles serviced starting from the starting point, and iii) to traverse the path starting from the depot to the termination point. A customer is served by one particular vehicle, another constraint is the vehicle should meet the time-window constraint; this should meet the requirements such as customer satisfaction, minimizing the cost, to find the optimal path. A penalty cost is provided for early or late arrivals that improvise customer fulfilment. The penalty obtained for late arrival is high in aspect of early arrival. When delivery is concerned taking into account several aspects involved with optimal distribution of path apart from goods requirement, refrigerated vehicle weight as well as time window is considered. Consider a graph $G = (V, A)$ a fully connected graph that depicts the network of the distribution of vehicles. Specifically V = {0, 1, 2, ….., n} be the set of nodes, where 0 represents the distribution center and 1, 2, 3, …….., n depicts the customer points. A= {(a, b): a, b∈N, a ≠ b} that depicts the routes. Considering the distribution center, customer location, and the demand known in prior. The distance is calculated between two customers (a, b) by Euclidean distance measure.

3.1. Cost evaluation

The cost of the vehicle consists of vehicle wear maintenance, the total expense, and the salary of the driver. Let g_h depict the used vehicle h. a_{xy}^{k} is a 0-1 decision variable where x_{ij}^{k} denotes that the vehicle k departs from the distribution center to the customer i and j, else a_{yz}^{x}=0. The vehicle fixed cost FC is by given (1). The customer's demand is used to estimate the distribution cost of the vehicle. TC Represents the burden per unit weight and d_{ab} the distance between the customers a and b, m^a denotes the cargo demand of the customer a. The transportation cost is mentioned in (2). The products, which are perishable, that consist of cargo damage from wear and tear the timestamp that at which the vehicle leaves the distributed center, the products that are delivered within specific time requirement. The cargo damage occurs within a time window as accepted by the customer. The association between the distance and damage coefficient grows exponentially; $\boldsymbol{\tau}$ is the declining co-efficient to detect the freshness of the product and t_i is the actual estimated time to reach the customer a and t_o the time window required by the customer. The total damage cost can be find by (3).

$$FC = \sum_{x=1}^{X} \sum_{y=1}^{n} \sum_{z=1}^{n} a_{yz}^{x}\, g_h \tag{1}$$

$$TC = \sum_{x=1}^{X} \sum_{y=1}^{n} \sum_{z=1}^{n} a_{yz}^{x}\, d_{ab} m^a \tag{2}$$

$$TDC = \sum_{x=1}^{X} \sum_{y=1}^{n} \sum_{z=1}^{n} a_{yz}^{x}\, d_{ab} m^a (1 - f^{-\tau_1(}t_i - t_o)) \tag{3}$$

3.2. Distribution cost

The measure of time the distribution center that responds to the requirements of the customer known as satisfaction. The expected time of the customer to deliver the goods, the satisfaction is higher, the expected time period of the customer in the interval is given by [f_a, l_a]. The arrival time is given by AT_a for the number of customers is given as n. the total satisfaction is considered as 100 for the delivery, the penalty denoted as $\boldsymbol{\delta}$, for early delivery penalty factor is denoted as δ_1 and for late delivery δ_2, here $\delta_1 < \delta_2$,the satisfaction of a single customer is termed as C_i is defined as (4), (5).

$$C_i = \{\frac{100}{n} - \delta_1 \frac{f_a - AT_a}{f_a}, if\ f_a > AT_a$$
$$\{\frac{100}{n},, if\ f_a < AT_a < l_a \quad (4)$$
$$\{\frac{100}{n} - \delta_2 \frac{AT_a - l_a}{l_a}, if\ l_a > AT_a$$

$$DC = 5\delta_1 \frac{f_a - AT_a}{f_a} + 10\delta_2 \frac{AT_a - S_a}{S_a} \quad (5)$$

3.3. Optimization of the ACO+graph network model

Various factors such as vehicle cost, distribution cost, and customer satisfaction cost is determined by (6), (7), (8). In (9) and (10) determines that each customer is serviced by one vehicle service. Equation (11) the delivery vehicle leave the distribution center for delivering the goods and then return back to the distribution center, in (12), the total weight of the goods indeed required by the customer could not exceed the load of the vehicle. In (13) we can say that the no of vehicles in the distribution center is limited. In (14) the relationship of customers from y to y+1. In (15) once the y-th customer is serviced the weight of the vehicle is estimated by d^y, the vehicle leaving the distribution enter is the same vehicle as the one returning the distribution center, the value taken by the decision variable should not be negative in the range 0-1, the time window wherein the delivery vehicle arrives late or early.

$$Min_{total} = FC + TC + TDC \quad (6)$$

$$Min_t = A_{ab}^x \frac{u_{ab}}{v_{ab}} (\gamma \left(\mu\, B_t + \frac{P_t}{n} + P_c\right)/\alpha)h \quad (7)$$

$$Max_t = \left[\frac{100}{N} - \mu_1 \frac{b_a - D_b}{b_a}\right] + \frac{100}{N} + \left[\frac{100}{N} - \mu_2 \frac{D_a - M_a}{M_a}\right] \quad (8)$$

$$\sum_{x=1,y=1}^{n} \sum_{x=1}^{X} a_{yz}^x = 1, \quad (9)$$

$$\sum_{y=1}^{n} \sum_{x=1}^{X} a_{qz}^x - \sum_{z=1}^{n} \sum_{x=1}^{X} a_{bz}^x = 0, b \in \text{n}, \quad (10)$$

$$\sum_{y=1}^{n} \sum_{x=1}^{X} a_{yo}^x = \sum_{y=1}^{n} \sum_{x=1}^{X} a_{oz}^x = X, \forall\, \text{y}, \text{z} \in \text{G}, \text{x} \in \text{X} \quad (11)$$

$$\sum_{y=1,}^{n} a_y^{xe} D^y \leq D_x^e, \forall\, x \in \text{X}, \text{e} \in E_X \quad (12)$$

$$\sum_{x=1}^{X} \sum_{z=1}^{n} a_z^x \leq \text{X}, \forall\, \text{x} \in \text{X} \quad (13)$$

$$\sum_{z=0}^{n} (D_{zy}^P - D_{yz}^P) = d^y, \forall (\text{y}, \text{z}) \in \text{G} \quad (14)$$

$$\begin{aligned} &\sum_{x=1}^{X} \sum_{z=0}^{n} a_{yz}^x = \sum_{x=1}^{X} \sum_{y,z=0}^{n} a_{zy,}^x\ \forall\, x, y \in G, x \in X, \\ &\text{d}_y \geq 0, \forall y \in G \\ &a_{yz}^x (1 - a_{yz}^x) = 0, \forall\, y, z \in \text{G}, \text{x} \in \text{X}, \\ &f_y \leq AT_y \leq l_y, \text{y} \in \text{n} \\ &f_y - AT_y > 0, \forall\, \text{y} \in \text{G} \\ &l_y - AT_y < 0 \forall\, \text{y} \in \text{G} \end{aligned} \quad (15)$$

Ant colony optimization technique is employed here to solve the optimization problems to understand the pattern of ants searching for food they find a short route from food to their particular nest they follow each other by releasing a chemical known as pheromone, the replication of their above procedure of the ants following the trail makes the trail more accurate. The algorithm proposed here to develop each vehicle for the respected duration of time window. This model can be applied to a multiple start point with multiple delivery points who source us to have a pickup and delivery source from source to destination while in the process of selecting the best node to the delivery point. We have chosen an algorithm here for selecting the appropriate route if it satisfies the particular criteria or it can select the next node until it fits into the constraints. Algorithm 1 displays the improvised ACO+graph network.

Algorithm 1. Improvised ACO+graph network

Step 1: *initialize the parameters, consisting of number of ants max, the number of levels is given as L_{max} , the pheromone repetitions is given by P_L, weights associated with pheromone level is given as μ and ρ. The max and min values of pheromone are given as β_{max} andβ_{min}.*

Step 2: *To place the m ants randomly,* initialization $Pheromone_{concentration}$, *considering the adjacent node based on given node.*

Step 3: *Updation and restriction of $Pheromone_{concentration}$, value between min and max of pheromone, transition probability of each node is obtained. Thereby visiting each node and completely visit all nodes.*

Step 4: *Estimate the total cost evaluation, calculate the optimized path for minimal cost and customer satisfaction by using the Pareto optimal principle, when N reaches the max value, the $Pheromone_{concentration}$ is initialized again.*

Step 5: *The value of N is less than the maximum, go to step 2 else finish the iteration, output the Pareto optimal principle and optimize the distribution path.*

3.4. Data and parameter selection

The dataset considered is Solomon standard considering 0 to 100 customers, considering the parameters like customer satisfaction, the time in which the goods are serviced in time window constraints. The ant colony optimization algorithm, the number of levels considered in $Pheromone_{concentration}$. The number of ants considered has a direct influence on the optimization of the path for effective transmission. The cost minimization needed to be considered for different levels in the ant colony optimization algorithm. VRP integrated along graph network, of multigraph-based model known as ACO+graph network model.

4. RESULTS AND ANALYSIS

4.1. Dataset details

The data is selected based on analysis of the Pareto optimum solution, which is the most effective solution to the multiple aims programming scenario. The best version of it suppresses the sub-objectives to achieve the main objective quickly. As a result, there is very little potential for conflict between objectives and sub-objectives, and a solution is obtained after noise removal. The proposed ACO+graph network method outperforms the competition in numerous test cases and 100 customers in three different circumstances. This information is organized in a Pareto optimal solution format. Because no one of the resolutions in the Pareto front has been subjugated through solutions which are outside, (or by solutions inside the Pareto front curve), the non- subjugated explanations have the few objective disruptions. This feature gives the decision-maker more options to choose from. Multi-objective optimization of cost, carbon emissions, and customer happiness is explored in this study, with the result determined as a Pareto optimal solution.

4.2. Result analysis

The analysis of result is carried out using the Pareto optimal solution, which concludes that project benefit of 80% work comes from 20% of work carried out. This is optimized further to state that the sub-objectives are curbed in effectively achieving the objective. Due to this issue, there is less scope to achieve the objectives and to obtain a solution without noise. The results are tested with test cases of 25, 50, 75, and 100 customers using the proposed approach to provide a better solution. The detailed description of each result is shown below. The abbreviations considered in graph are: cost in CNY (C(CNY), carbon emissions (CE), customer satisfaction (CS), and number of vehicles used (NY).

4.3. Test case for 25 customers

The path is optimized to achieve efficient performance for the C101 (25) to obtain the results using Pareto optimal principle. We can find from the graph that the algorithm ACO+graph theory gives better results in comparison with that of other state-of-art-techniques. Figure 2 shows the comparison of ACO+graph network, ACOMO, ACO for c101_25 customers. The proposed algorithm ACO+graph network which sums up the total cost to 3,139, the vehicle used to get an optimal path is (0, 5, 3, 7, 8, 10, 11, 9, 6, 4, 2, 1, and 0), (0, 13, 17, 18, 19, 15, 16, 14, 12, 0) and (0, 20, 24, 25, 23, 22, 21, 0). Figure 3 displays the solution for c101 with 25 customers.

4.4. Test case for 50 customers

The analysis here is carried out on the test set for 50 customers with c101 (50), 5 vehicles have been deployed with the paths considered. The total cost estimated here sums up to 5943. Figure 4 displays comparison of ACO+graph network, ACOMO, ACO for c101_50 customers. Figure 5 displays the solution for c101 with 50 customers. Optimal path is (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), (0, 13, 17, 18, 19, 15, 16, 14, 12, 0).

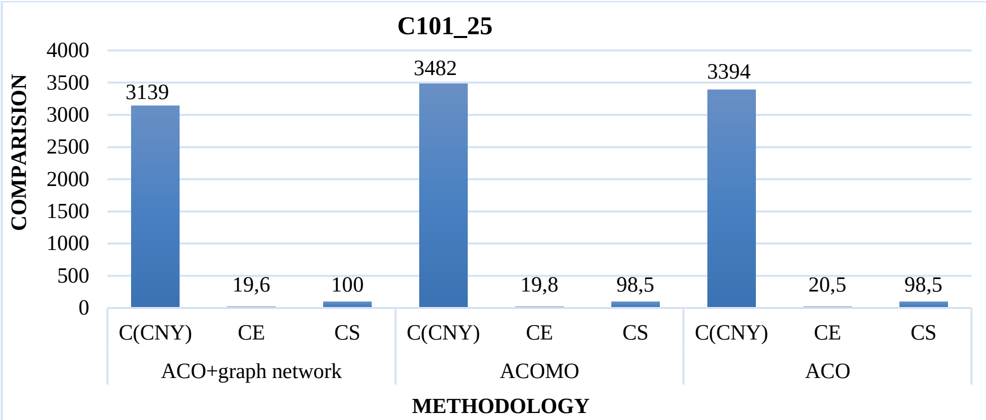

Figure 2. Comparison of ACO+graph network, ACOMO, ACO for c101_25 customers

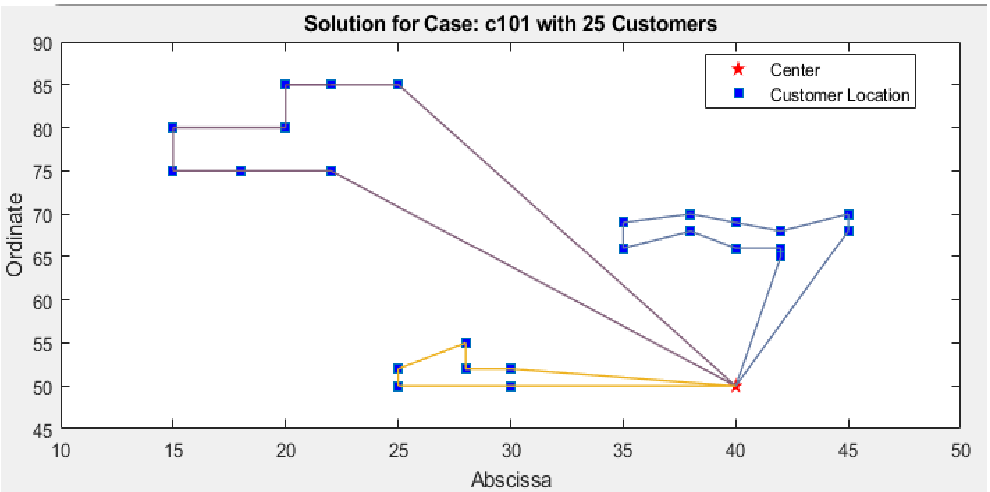

Figure 3. Solution for c101 with 25 customers

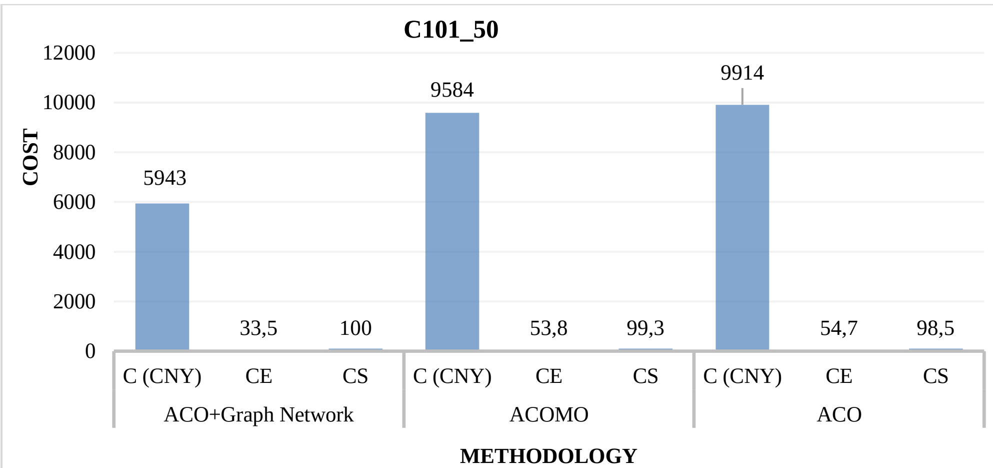

Figure 4. Comparison of ACO+graph network, ACOMO, ACO for c101_50 customers

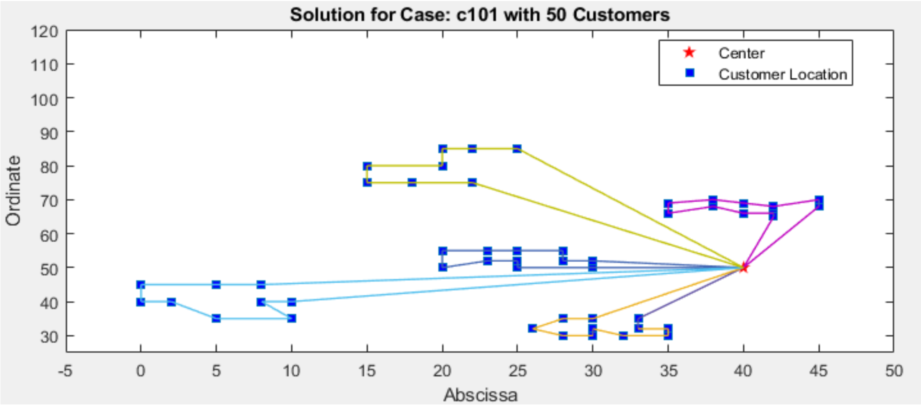

Figure 5. Solution for c101 with 50 customers

4.5. Test case for 75 customers

The test dataset used here is c101 (75) has been used for analysis. To optimize an efficient path 8 number of vehicles are used for the analysis of results. Figure 6 displays the comparison of ACO+graph network, ACOMO, ACO for c101_75 customers. Figure 7 shows the solution for c101 with 75 customers. Optimal path is (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)

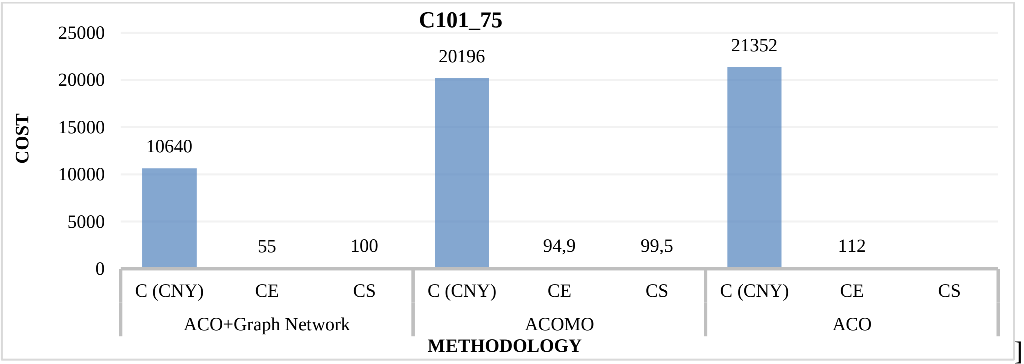

Figure 6. Comparison of ACO+graph network, ACOMO, ACO for c101_75 customers

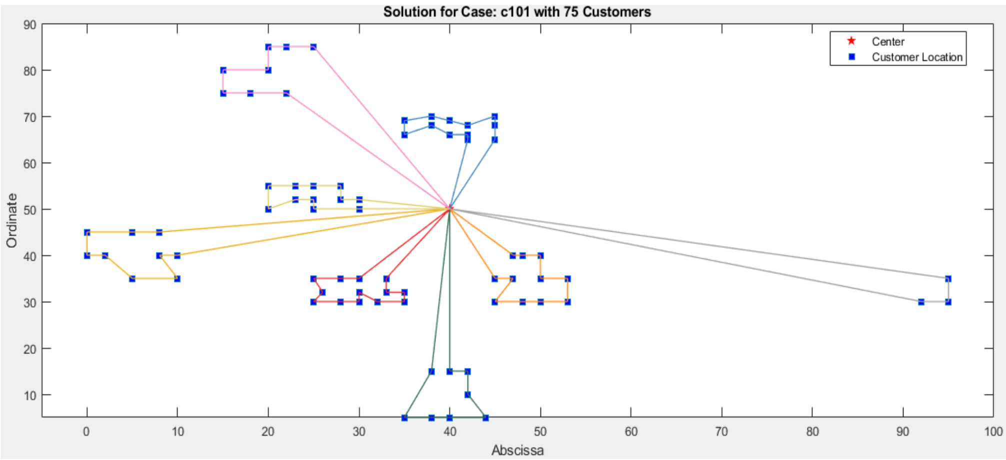

Figure 7. Solution for c101 with 75 customers

4.6. Test case for 100 customers

The test set used here is c101 (100) dataset. The total cost achieved is 1362 by deploying 10 vehicles, to choose the most optimal path. Below mentioned Figure 8 shows comparison of ACO+graph network, ACOMO, ACO for c101_100 customers. Figure 9 shows the solution for c101 with 100 customers. Optimal path is (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).

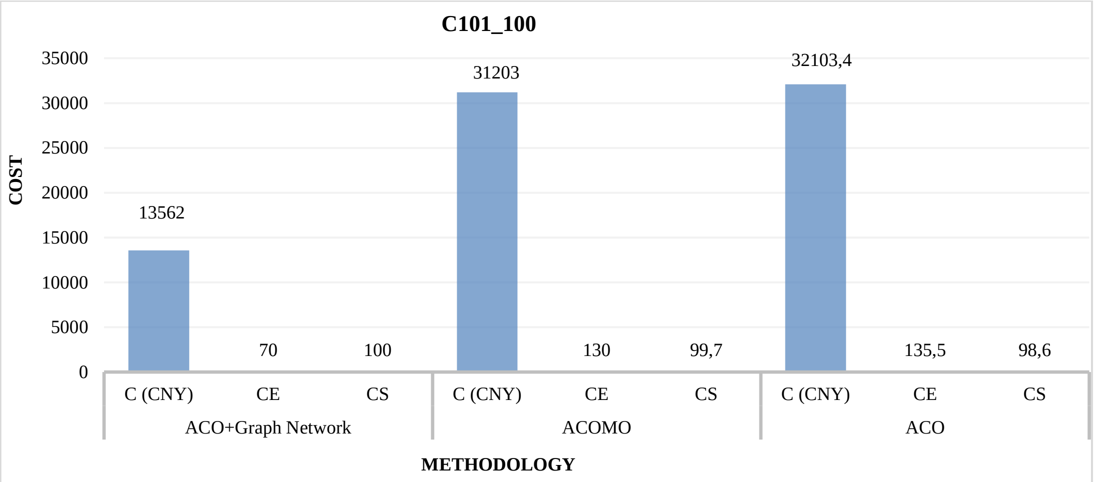

Figure 8. Comparison of ACO+graph network

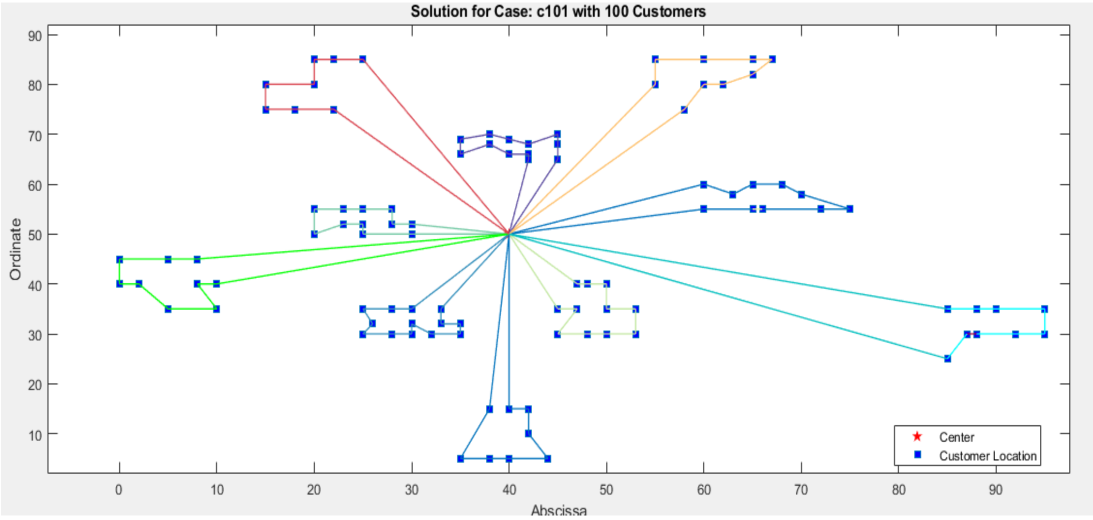

Figure 9. Solution for c101 with 100 customers

By comparison of this results with other state-of-art-techniques we can conclude that our proposed ACO+graph network performs better with other existing methods, by employing a smaller number of vehicles for to achieve effective performance by minimizing the cost value and the proposed system shows the effective performance to be countered with real-world problems. Our proposed system shows the total in reducing the cost management purposes, for modified ACO+graph network algorithm. This technique outperforms the ACO algorithm.

5. CONCLUSION

This paper here involves combining the features of graph theory and ACO to solve the vehicle routing problem with time window constraints. Implementing the task solution for optimal path using the graph-based network, here we try to integrate the VRP problem with time window constraints by merging it with the graph network. Our proposed model works effectively in comparison with other state of art techniques. The VRP problem while considering other measures such as minimizing cost, and optimal path to achieve better performance. A multi-objective optimization model is achieved in a real-time scenario, and an improved ACO algorithm integrated along with a graph network is considered here for satisfying the customers by delivering the goods in a specific time window. We have used Pareto optimal principle over here for multi-objective optimization. Future work to be carried out here suggests that we consider other parameters like temperature for perishable goods; this also establishes the amount of energy consumed by the vehicle during transportation of goods from source to destination.

REFERENCES

[1] A. L. Kok, E. W. Hans, and J. M. J. Schutten, "Vehicle routing under time-dependent travel times: the impact of congestion avoidance," *Computers and Operations Research*, vol. 39, no. 5, pp. 910–918, May 2012, doi: 10.1016/j.cor.2011.05.027.
[2] Z. Wang, Z. Hu, and X. Yang, "Multi-agent and ant colony optimization for ship integrated power system network reconfiguration," *Journal of Systems Engineering and Electronics*, vol. 33, no. 2, pp. 489–496, Apr. 2022, doi: 10.23919/JSEE.2022.000048.
[3] J. Müller, "Approximative solutions to the bicriterion vehicle routing problem with time windows," *European Journal of Operational Research*, vol. 202, no. 1, pp. 223–231, Apr. 2010, doi: 10.1016/j.ejor.2009.04.029.
[4] S. N. Kumar and R. Panneerselvam, "A survey on the vehicle routing problem and its variants," *Intelligent Information Management*, vol. 04, no. 03, pp. 66–74, 2012, doi: 10.4236/iim.2012.43010.
[5] K. Braekers, K. Ramaekers, and I. V. Nieuwenhuyse, "The vehicle routing problem: state of the art classification and review," *Computers and Industrial Engineering*, vol. 99, pp. 300–313, Sep. 2016, doi: 10.1016/j.cie.2015.12.007.
[6] B. Eksioglu, A. V. Vural, and A. Reisman, "The vehicle routing problem: a taxonomic review," *Computers and Industrial Engineering*, vol. 57, no. 4, pp. 1472–1483, Nov. 2009, doi: 10.1016/j.cie.2009.05.009.
[7] R. Elshaer and H. Awad, "A taxonomic review of metaheuristic algorithms for solving the vehicle routing problem and its variants," *Computers and Industrial Engineering*, vol. 140, p. 106242, Feb. 2020, doi: 10.1016/j.cie.2019.106242.
[8] G. D. Konstantakopoulos, S. P. Gayialis, and E. P. Kechagias, "Vehicle routing problem and related algorithms for logistics distribution: a literature review and classification," *Operational Research*, vol. 22, no. 3, pp. 2033–2062, Jul. 2022, doi: 10.1007/s12351-020-00600-7.
[9] S. Dobzinski, N. Nisan, and M. Schapira, "Approximation algorithms for combinatorial auctions with complement-free bidders," in *Proceedings of the Annual ACM Symposium on Theory of Computing*, New York, NY, USA: ACM, May 2005, pp. 610–618. doi: 10.1145/1060590.1060681.
[10] U. Feige, "On maximizing welfare when utility functions are subadditive," in *Proceedings of the Annual ACM Symposium on Theory of Computing*, New York, NY, USA: ACM, May 2006, pp. 41–50. doi: 10.1145/1132516.1132523.
[11] Z. Friggstad, "Multiple traveling salesmen in asymmetric metrics," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2013, pp. 173–188. doi: 10.1007/978-3-642-40328-6_13.
[12] Z. Friggstad, M. R. Salavatipour, and Z. Svitkina, "Asymmetric traveling salesman path and directed latency problems," *SIAM Journal on Computing*, vol. 42, no. 4, pp. 1596–1619, Jan. 2013, doi: 10.1137/100797357.
[13] T. Qasim *et al.*, "An ant colony optimization based approach for minimum cost coverage on 3-D Grid in wireless sensor networks," *IEEE Communications Letters*, vol. 22, no. 6, pp. 1140–1143, Jun. 2018, doi: 10.1109/LCOMM.2018.2819643.
[14] J. Lv, X. Wang, and M. Huang, "Ant colony optimization-inspired ICN routing with content concentration and similarity relation," *IEEE Communications Letters*, vol. 21, no. 6, pp. 1313–1316, Jun. 2017, doi: 10.1109/LCOMM.2016.2631515.
[15] Y. Sun, W. Dong, and Y. Chen, "An improved routing algorithm based on ant colony optimization in wireless sensor networks," *IEEE Communications Letters*, vol. 21, no. 6, pp. 1317–1320, Jun. 2017, doi: 10.1109/LCOMM.2017.2672959.
[16] Y. Li, Z. Gao, and J. Li, "Vehicle routing problem in dynamic urban traffic network," in *8th International Conference on Service Systems and Service Management - Proceedings of ICSSSM'11*, IEEE, Jun. 2011, pp. 1–6. doi: 10.1109/ICSSSM.2011.5959534.
[17] M. López-Ibáñez and T. Stützle, "An analysis of algorithmic components for multiobjective ant colony optimization: A case study on the biobjective TSP," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2010, pp. 134–145. doi: 10.1007/978-3-642-14156-0_12.
[18] F. Dahan, K. El Hindi, A. Ghoneim, and H. Alsalman, "An enhanced ant colony optimization based algorithm to solve QoS-aware web service composition," *IEEE Access*, vol. 9, pp. 34098–34111, 2021, doi: 10.1109/ACCESS.2021.3061738.
[19] D. Zhang, X. You, S. Liu, and K. Yang, "Multi-colony ant colony optimization based on generalized jaccard similarity recommendation strategy," *IEEE Access*, vol. 7, pp. 157303–157317, 2019, doi: 10.1109/ACCESS.2019.2949860.
[20] M. Xu, X. You, and S. Liu, "A novel heuristic communication Heterogeneous dual population ant colony optimization algorithm," *IEEE Access*, vol. 5, pp. 18506–18515, 2017, doi: 10.1109/ACCESS.2017.2746569.
[21] W. Liu, "Route optimization for last-mile distribution of rural e-commerce logistics based on ant colony optimization," *IEEE Access*, vol. 8, pp. 12179–12187, 2020, doi: 10.1109/ACCESS.2020.2964328.
[22] H. Zhu, X. You, and S. Liu, "Multiple ant colony optimization based on pearson correlation coefficient," *IEEE Access*, vol. 7, pp. 61628–61638, 2019, doi: 10.1109/ACCESS.2019.2915673.
[23] M. Liu, X. You, X. Yu, and S. Liu, "KL Divergence-based pheromone fusion for heterogeneous multi-colony ant optimization," *IEEE Access*, vol. 7, pp. 152646–152657, 2019, doi: 10.1109/ACCESS.2019.2948395.
[24] Y. H. Jia, Y. Mei, and M. Zhang, "Confidence-based ant colony optimization for capacitated electric vehicle routing problem with comparison of different encoding schemes," *IEEE Transactions on Evolutionary Computation*, vol. 26, no. 6, pp. 1394–1408, Dec. 2022, doi: 10.1109/TEVC.2022.3144142.

[25] D. Z. Zhu, P. L. Werner, and D. H. Werner, "Design and optimization of 3-D frequency-selective surfaces based on a multiobjective lazy ant colony optimization algorithm," *IEEE Transactions on Antennas and Propagation*, vol. 65, no. 12, pp. 7137–7149, Dec. 2017, doi: 10.1109/TAP.2017.2766660.
[26] J. Liu, Y. Wang, G. Sun, and T. Pang, "Multisurrogate-assisted ant colony optimization for expensive optimization problems with continuous and categorical variables," *IEEE Transactions on Cybernetics*, vol. 52, no. 11, pp. 11348–11361, Nov. 2022, doi: 10.1109/TCYB.2021.3064676.
[27] R. Baldacci, A. Mingozzi, and R. Roberti, "New state-space relaxations for solving the traveling salesman problem with time windows," *INFORMS Journal on Computing*, vol. 24, no. 3, pp. 356–371, Aug. 2012, doi: 10.1287/ijoc.1110.0456.
[28] K. Doerner, M. Gronalt, R. F. Hartl, M. Reimann, C. Strauss, and M. Stummer, "Savings ants for the vehicle routing problem," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2002, pp. 11–20. doi: 10.1007/3-540-46004-7_2.
[29] E. Demir, T. Bektaş, and G. Laporte, "An adaptive large neighborhood search heuristic for the pollution-routing problem," *European Journal of Operational Research*, vol. 223, no. 2, pp. 346–359, Dec. 2012, doi: 10.1016/j.ejor.2012.06.044.
[30] D. C. Paraskevopoulos, P. P. Repoussis, C. D. Tarantilis, G. Ioannou, and G. P. Prastacos, "A reactive variable neighborhood tabu search for the heterogeneous fleet vehicle routing problem with time windows," *Journal of Heuristics*, vol. 14, no. 5, pp. 425–455, Oct. 2008, doi: 10.1007/s10732-007-9045-z.

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