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Solving a Multi-Conveyance Travelling Salesman Problem using an Ant Colony Optimization Method

Moumita Mondal[1]*, **Durgesh Srivastava**[2]

1 Department of Computer Science and Engineering, Shri JJT University, Jhunjhunu, 333010, Rajasthan, India
2 Department of Computer Science & Engineering, Chitkara University Institute of Engineering & Technology, Chitkara University, Rajpura, 140401, Punjab, India

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* **Corresponding author**.

moumitamj12@gmail.com

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Abstract

Objectives: A well-known NP-complete problem is the travelling salesman problem (TSP). It has numerous engineering and scientific applications. In this article, we have proposed a multi-conveyance TSP where different conveyances are present to travel from one city to another city. This is an extension to classical TSP. In this TSP, the salesman visits all the cities only once during his/her tour, using different conveyances to travel from one city to another. The cost of travelling between cities using various modes of conveyance varies. The objective of this research is to find the minimum cost tour using an ant colony optimization (ACO) based approach by satisfying the constraints of the proposed multi-conveyance TSP. **Method:** The considered TSP has been solved using a novel ACO technique. The proposed ACO is adopted with the Roulette-wheel selection and "tuning solution" techniques. We have used a few benchmark datasets from TSPLIB to check the effectiveness of the proposed algorithm. The experimental findings for a few benchmarks TSP instances show that almost always, the proposed ACO is able to find a better result. Then, we used some redefined and randomly generated datasets for experiments. The experimental outcomes for various input datasets are also very encouraging. **Findings:** The goal of the proposed TSP is to find a complete tour with a minimum cost without exceeding the total travel cost and total travel time. Thus, there are two novel constraints in the classical TSP. **Novelty:** A unique aspect of the proposed research is the use of several conveyance facilities and a fixed total travel time and cost. This is new, as these three factors are integrated into a single TSP model.

Keywords: Travelling Salesman Problem; Travel Cost; Travel Time; MultiConveyance TSP; Ant Colony Optimization

1 Introduction

The travelling salesman problem (TSP) consists of a set of cities and the distance between each pair of cities. The goal is to determine the shortest path that makes exactly one stop in each city before returning to the starting point. The proposed multiple conveyances travelling salesman problem is an extension of this problem in which several conveyance facilities are available to travel from city to city. The cost and time for travelling using different modes of conveyance from one city to another are different. In the proposed TSP, there are different conveyance facilities to travel from one city to another, and that is the main attraction of this model. If we consider a real-life situation, such that a medical representative (MR) travels and meets some doctors in different cities with a suitable conveyance type then the proposed TSP is effective. For example, if a traveller takes a superfast train from x-city to y-city, the trip will be cheaper and less expensive than if he takes a local train. The traveller will take the decision as per the traveller's allowance of travel. The proposed TSP can be used to solve this problem.

In artificial intelligence, optimization, logistics, and other applications, combinatorial optimization is one of the most studied disciplines. A novel local search heuristic has been developed for solving Euclidean TSP based on nearest insertion into the convex hull construction heuristic[(1)]. The travelling salesman problem has been solved by genetic algorithms (GA) by comparing the results of implementing two different types of two-point (1 order) gene crossover, the static and the dynamic approaches, which are used to produce new offspring[(2)]. The implementation of the tissue P system allows the researchers to analyze and verify some behavioural aspects with costs[(3)]. The robustness of the TSP routes is investigated by recognising the special combinatorial structures of Kalmanson matrices based on the procedures of producing three lower bounds which provide guarantees on the optimality of the solutions[(4)]. A population-based harmony search approach was adapted to solve the asymmetric travelling salesman problem[(5)]. The researchers have conducted experiments with different time window sizes and determined their impact on tour duration, customer satisfaction, and solution time of the optimal routes[(6)]. A new migration strategy has been used to improve the performance of the parallel genetic algorithm in solving various travelling salesman problems[(7)]. A two-phase ant colony optimization based approach has been developed for the single depot multiple travelling salesman problem[(8)]. A selective generalised TSP has been introduced to determine the maximum profitable tour within the given threshold of the tour's duration, which consists of a subset of clusters and a subset of nodes in each cluster visited on the tour[(9)]. An improved ant colony optimization has been developed for the travelling salesman problem with an adaptive heuristic factor[(10)]. A memetic algorithm has been developed for the asymmetric travelling salesman problem[(11)]. An efficient harris hawk optimization algorithm has been developed for solving the travelling salesman problem[(12)].

In the Euclidean TSP[(13)], there is a given set of points P in the plane and a set of n connected regions, each containing at least one point of P. The aim is to minimize the distance or time of travel, where the distance between two points is given by the Euclidean distance. The Euclidean distance obeys the triangle inequality, so the Euclidean TSP forms a special case of metric TSP. A geometric transformation of Euclidean TSP tours defines a novel formulation of TSP. This change makes it possible to determine the TSP's defining geometric parameters and to investigate novel heuristics based on the addition of new constraints[(13)]. For the purpose of resolving the symmetric travelling salesman problem, a novel approach using permutation rules and a genetic algorithm is put forth[(14)]. An adaptive insertion heuristic has been developed to solve multiple TSP with drone[(15)]. The multiple TSP with time windows is solved using a GA. This study builds a model for cold chain logistics and route optimization that has low transportation, carbon, and refrigeration costs[(16)]. An ant colony optimization algorithm has been introduced for the travelling salesman problem with dynamic demands[(17)]. Travelling salesman problem has also been solved using a new modified genetic algorithm with a new special initialization of population[(18)]. The travelling salesman problem with time windows has been thoroughly examined by the researchers in the context of its solution on a quantum computer[(19)]. Recently, an improved ACO-based method with adaptive visibility has been intelligently adopted to solve TSP[(20)]. A multi-approach to the travelling salesman problem has also been solved by an ACO with multiple colonies[(21)]. ACO and simulated annealing algorithms have been hybridised in the literature to solve dynamic TSP[(22)]. Recently a TSP has been solved by an adaptive ant colony optimization with node clustering[(23)]. A transfer learning-based particle swarm optimization algorithm has been developed for the travelling salesman problem[(24)].

1.1 Research gap

Different modes of transportation between cities have different standpoints and journey times. Although research has been done for multiple conveyance TSP where two objectives are considered[(25)]. Apart from this research, we have considered multiple conveyances TSP with a predetermined total travelling cost and time. None the less, we have considered novel ACO instead of evolutionary algorithms[(25)]. The overall costs of travel as well as the amount of time it takes to complete a tour are both predetermined. The originality of the proposed TSP model is the projected research with different conveyance facilities and a fixed total travel time and cost. No researcher has, as far as we are aware, combined all three aspects into a single TSP model. The usage of "tuning solution" in the suggested version of ACO is another innovative feature of this research. After the ants have completed the maximum number of iterations, the "tuning solution" procedure determines the closest better neighbour solution for each of the complete paths.

In this paper, we have proposed a multi-conveyance TSP with limited cost and time. The main contributions of the paper are:

1. For each pair of cities, multiple modes of transportation are available.
2. The travel cost and time for different modes of transportation between cities differ.
3. Simultaneously, the total travel cost and travel time for a complete tour are fixed.
4. The proposed research with multiple conveyance facilities along with a fixed total travel time and cost is a novelty of the proposed research. As far as we are aware, no researcher has combined these three factors into a single TSP model.
5. Another novelty of this research is that the authors have developed a modified version of ACO by adopting a new feature, namely ”tuning solution”.

The rest of this paper is organized as follows. We discussed the problem's practical significance in subsection 1.2. In subsection 1.3, we define the suggested problem in detail. Section 2 describes the proposed problem's algorithm. The findings of the experiments are presented in Section 3. Section 4 brings the paper to a close.

1.2 Practical significance of the problem

In a real-life scenario, the cost of travel varies depending on the time of day, weather, and traffic conditions. As a result, the cost of travel between two cities cannot be calculated in this situation. To handle the ambiguity in the cost and time estimation of TSP, the decision maker introduces tolerance. However, the cost of travelling from one node to another is determined by the mode of transportation used. It also fluctuates slightly based on the availability of the mode of transportation, the state of the road, and other factors, albeit its value usually falls within a range. Because these estimates are based on an expert's opinion, they are less prone to inaccuracy. Furthermore, the problem should be treated in such a way that a salesman can visit multiple cities utilizing various modes of transportation.

1.3 Problem definition

1.3.1 Classical TSP with cost and time limit constraints

In a classical two-dimensional travelling salesman cities using minimum cost. Let c(i,j) be the cost for travelling fromi-th city to j-th city. Total cost limit is Cost_{MAX} and time limit is Time. $_T$hen the problem can be mathematically formulated as:

$$\left.\begin{array}{c} \text{Minimize } Z=\sum_{i=1}^{N}\sum_{j=1}^{\mathrm{N}} y_{ij}c(i,j) \\ \text{subject to } \sum_{i=1}^{N} y_{ij}=1 \text{ for } j=1,2,\ldots,N \\ \sum_{j=1}^{N} y_{ij}=1 \text{ for } i=1,2,\ldots,N \\ \sum_{i=1}^{N}\sum_{j=1}^{\mathrm{N}} y_{ij}c(i,j)\leq \text{Cost}_{MAX} \\ \sum_{i=1}^{N}\sum_{j=1}^{\mathrm{N}} y_{ij}t(i,j)\leq \text{ Time }_{MAX} \end{array}\right\} \tag{1}$$

where y_{ij} = 1 if the salesman travels from city-i to city-j, otherwise y_{ij} = 0 and; Cost_{MAX} and Time_{MAX} are the maximum cost limit and time limit of the tour, respectively. Let (x_1, x_2, ..., x_N, x_1) be a complete tour of a salesman, where $x_i \in \{1,\ 2,\ \ldots,\ N\}$ for i = 1, 2, ..., N and all x_i are distinct. Then the above problem reduces to:

$$\left.\begin{array}{c} \text{Determine a complete tour } (\mathrm{x1},\mathrm{x2},\ldots,\mathrm{xN},\mathrm{x1}) \\ \text{to minimize } Z=\sum_{i=1}^{N-1}\operatorname{co}(x_i,x_{i+1})+\operatorname{co}(x_N,x_1) \\ \text{subject to } \sum_{i=1}^{N-1}\operatorname{co}(x_i,x_{i+1})+\operatorname{co}(x_N,x_1)\leq \text{Cost}_{MAX} \\ \text{and } \sum_{i=1}^{N-1}\operatorname{tm}(x_i,x_{i+1})+\operatorname{tm}(x_N,x_1)\leq \text{ Time }_{MAX} \end{array}\right\} \tag{2}$$

where co(i,j) and tm(i,j) are the travel cost and time, respectively, for travelling from the i-th city to the j-th city.

1.3.2 Multi-conveyance TSP with time limit constraint

In a multi-conveyance travelling salesman problem, a salesman must travel between N cities for the least amount of cost by taking any of the M available modes of transportation. In his/her trip, the salesman begins in one city, visits all of the cities exactly once using the best mode of transportation available in each city, and then returns to the starting city for the least amount of cost. Travelling from one city to another using various modes of transportation has varied costs and times. Let co(i, j, k) and tm(i, j, k) be the cost and time, respectively, it takes to travel from i-th city to j-th city using the k-th type of conveyance. The salesperson must then determine a complete tour ($x_1, x_2, ..., x_N, x_1$) in which a specific or different combination of conveyance types ($con_1, con_2, ..., con_N$) is to be employed for the tour, where $x_i \in (1, 2, \ldots, N\}$ for i = 1, 2, ..., N, $con_i \in (1, 2, \ldots, M\}$ and all x_i 's are distinct. The problem can then be expressed numerically as:

$$\left.\begin{array}{l}\text{Determine a complete tour } (x1, x2, \ldots, xN, x1) \\ \text{and corresponding conveyance types } (\text{con}1, \text{con}2, \ldots, \text{conN}) \\ \text{to minimize } Z = \sum_{i=1}^{N-1} \cos(x_i, x_{i+1}, \text{con}_i) + \text{co}(x_N, x_1, \text{con}_N) \\ \text{subject to } \sum_{i=1}^{N-1} \text{co}(x_i, x_{i+1}, \text{con}_i) + \text{co}(x_N, x_1, \text{con}_N) \leq \text{Cost}_{MAX} \\ \text{and } \sum_{i=1}^{N-1} \text{tm}(x_i, x_{i+1}, \text{con}_i) + \text{tm}(x_N, x_1, \text{con}_N) \leq \text{Time}_{MAX}\end{array}\right\} \quad (3)$$

where Cost_{MAX} and Time_{MAX} are the maximum travel cost and time limit of a complete tour, respectively, that should be maintained by the salesman.

2 Methodology

2.1 Proposed ACO algorithm

In 1992, based on observations of ants' foraging behaviour and their ability to locate the shortest path between their colony and food sources[26],created an algorithmic model to solve a combinatorial optimization issue. Since then, there has been a surge in interest in developing ant-based algorithms, resulting in a significant variety of algorithms and applications[27].A chemical trail termed pheromone is left on the ground by ants throughout their travels. The original ACO method[28] is somewhat modified as shown below.

Basic steps of the proposed ACO:

1. Start
2. Initialize parameters
3. Initialize pheromone
4. For i = 1 to MaxIt (Maximum number of iterations)
5. For j = 1 to NOANT
6. Construct path for each ant
7. End for
8. Perform evaporation
9. Perform pheromone update for each ant's path.
10. End for
11. Tuning solution
12. End

2.2 ACO procedures for the proposed TSP variant:

(a) Representation: The number of ants in the system is represented by the integer variable N. PATH[n][N] is a two-dimensional integer array that represents the pathways of several ants. The path of the k-th ant is represented by PATH[k]. PATH[k][1] denotes the first node to be visited, PATH[k][2] the second node to be visited, and so on, with PATH[k][N] denoting the last node to be visited by the ant-k. Another two-dimensional integer array VEH[n][N] is used in multi-conveyance TSP to represent the various modes of transportation employed by different ants to travel between nodes. VEH[k][i] is the mode of transportation utilised by the k-th ant to get from the i-th node (PATH[k][i]) to the (i + 1)-th node (PATH[k][i + 1]).

(b) Initialization of pheromone: As the aim of a TSP is to minimize the cost, it is assumed that the initial value of pheromone is inversely proportional to the travel cost.

Because the goal of a TSP is to reduce costs, the initial value of r_{ij} = 1/C(i, j) is assumed for pair (i, j). Similarly for multi-conveyance TSP, it is assumed as r_{ijk} = 1/C(i, j, k) using multi-conveyance TSP for i-th city to j-th city using k-th type of conveyance. C(i, j, k) is the cost of travelling from i-th city to j-th using k-th type of conveyance.

(c) Create path: PATH[k][l] = i indicates that the l-th position of k-th ant is i-th node. Then the next node j∈NODE is to be selected by the ant with a probability p_{ijv}, such that the formula for selecting the next node using conveyance v with a probability p_{ijv} is (Engelbrech[27]):

$$p_{ijv} = \frac{T_{ivj}^{\alpha}}{\sum_{j \in NODE} \sum_{v=1}^{M} T_{ijv}^{\alpha}}$$

where α is a positive value in the range of[1,2]. We use Roulette-Wheel selection process for select the node. Here, for solve the multi-conveyance TSP, the value of α is assumed as 1.6 (Engelbrech [27]).

(d) Evaporation of pheromone: The following formulas are used for pheromone evaporation

$$\tau_{ijk} = (1-\rho)\tau_{ijk}$$

with $\rho \in [0,1]$. The constant, ρ, determines the rate at which pheromone evaporates. Here, we have set the value of ρ to 0.02. This parameter value is set by random experiment.

(e) Update of pheromone: Pheromone is increased on the trails through which the ants move once all of the ants have completed their journey. Say COST(k) is the cost of PATH[k], and for this path $\tau_{PATH(k](i]PATH(K](I+1]VEH(k][i]}$is increased by 1/COST(k). This formula is employed because our goal is to minimize the travel cost. Similarly for multi-conveyance TSP, if COST(k) be the cost of (PATH[k], VEH[k]), is increased by 1/COST(k).

(f) Tuning solution: After finding the best solution from an ant with a ”MaxIt” number of iterations, a ”Tuning solution” operation is performed. A ”tuning solution” is performed for each path or solution of the colony. Every two adjacent cities are interchanged in this operation. The process can be explained as follows:

1. For k = 1 to Noant do
2. Calculate the objective value of k-th ant, say BEFORETOBJ;
3. For l = 1 to N-1 do
4. Swap the pair of elements PATH[k][l] and PATH[k][l+1]
5. Calculate the objective value after swapping, say TEMPOBJ
6. If (TEMPOBJ< BEFORETOBJ then
7. Replace the k-th ant's path by the path after swapping (PATH[k][l] and PATH[k][l+1]
8. End if
9. End for
10. Find objective value of PATH for k-th ant, say KTOBJ
11. End For

(Here, Noant is the number of ant and N is the number of city)

The number of ants (Noant) and the maximum number of iteration is set by random experiment for different instances.

3 Result and Discussion

In this section, first of all we have considered some benchmark instances of TSPLIB and compared with that available in existing literature. In the next subsection, we have redefined a benchmark instance for the proposed problem and computed the results.

3.1 Performance analysis of the proposed algorithm

We used various benchmark asymmetric TSP situations reported by the existing literature [29] to demonstrate the usefulness of the proposed technique. From the said literature [29], we only investigated a few (of all) asymmetric TSP situations. The results of the proposed ACO algorithm are compared to the results of a bat algorithm with best tour, average tour, and standard deviation. The number of ants and the maximum number of iterations due to distinct instances are listed in the result table for these trials. The proposed ACO takes the values of α and σ as 1.7 and 0.01, respectively, for pheromone update and evaporation. The maximum number of iterations is 1000 for all the cases. The number of ants is 50 for br17, ftv35, and ftv38; and 70 for ftv70.

From Table 1 , we have observed that in all the cases, the proposed ACO gives better or the same output for the considered instances. For br17, ftv35, and ftv38, the proposed ACO computes optimal results as given in the literature [29]. For ftv70, the proposed ACO computes better results up to 1000 iterations. So, we conclude that the proposed ACO algorithm is one of the competitive algorithms to solve asymmetric TSP instances.

Now we have considered two instances in Table 2 , namely, ftv34 and ry48p to show the effectiveness of using the ”tuning solution” feature in ACO. We have presented the objective value obtained by using ”tuning solution” and without using ”tuning solution” in the ACO algorithm up to 500 iterations. Other parameters of the proposed ACO for these experiments are the same as in previous experiments of this subsection.

From Table 2 we have observed that for the considered two benchmark instances, the proposed ACO using ”tuning solution” computes a better result than the ACO without using ”tuning solution”. So we conclude that the ”tuning solution” operator in ACO is fruitful in solving the TSP instance.

Table 1. Comparisons of results using TSPLIB instances

Instance name	Optimal value	Parameters		IBA [29]			Proposed ACO		
				Best result	Average result	Standard deviation	Best result	Average result	Standard deviation
br17	39	Noants: MaxIt: 500	40	39	39	0	**39**	**39**	**0**
ftv35	1473	Noants: MaxIt: 1000	40	1473	1493.7	8.0	**1473**	**1309.50**	**4.97**
ftv38	1530	Noants: MaxIt: 1000	40	1530	1562.0	13.79	**1530**	**1549.45**	**3.8**
ftv70	1950	Noants: MaxIt: 1000	70	2111	2233.2	48.8	**1995**	**2256.35**	**6.85**

Table 2. Results demonstrate the effectiveness of the ”tuning solution” feature in the proposed ACO

Instance name	Number of iterations	Result by the proposed ACO without using “tuning solution” feature	Result by the proposed ACO with using “tuning solution” feature
ftv34	500	1358	1332
ry48p	500	15322	15012

3.2 Experiment with redefined datasets for the proposed TSP

Now we have redefined a few instances of TSPLIB. The proposed TSP has two parameters, namely, cost and time, respectively. A cost matrix is considered from TSPLIB and a time matrix is generated in the range [7,26]. Here we have considered three types of conveyance. The cost of travel from i-th city to j-th city using the second type of conveyance is the same as in TSPLIB; and to obtain the cost using the first and third types, any random number in the range [1,3] is subtracted and added, respectively. The time of travel using three types of conveyance from i-th city to j-th city is a random number in the range of [7,26]. The number of ants and the maximum number of iterations are given in the result table.

Table 3. Result of redefined datasets for the proposed multi-conveyance TSP

Instance	Size of problem	Input parameters	Result
Redefined ftv33	34	Number of ants: 30 Maximum iterations: 1000 Cost limit:1330, Time limit:300	Objective/cost: 1329.96 Time: 294.87
Redefined ftv35	36	Number of ants: 30 Maximum iterations: 1000 Cost limit:1500, Time limit:330	Objective/cost: 1454.53 Time: 321.84
Redefined ftv70	70	Number of ants: 60 Maximum iterations: 1000 Cost limit:2100, Time limit:900	Objective/cost: 2019.18 Time: 883.96

Table 4. Output tour for multi-conveyance TSPs

Redefined ftv33	(1; 1), (14; 1), (17; 1), (16; 1), (15; 1), (13; 1), (10; 1), (33; 1), (8; 1), (9; 1), (11; 1), (12; 1), (32; 1), (19; 1), (20; 1), (21; 1), (22; 1), (23; 1), (27; 1), (28; 1), (29; 1), (30; 3), (26; 1), (25; 1), (24; 2), (18; 2), (5; 1), (7; 1), (6; 1), (31; 3), (34; 1), (3; 1), (4; 1), (1; 1)
Redefined ftv35	(1; 1), (14; 1), (13; 1), (6; 1), (8; 1), (7; 1), (5; 1), (33; 1), (31; 1), (28; 1), (24; 1), (21; 1), (22; 1), (23; 1), (29; 1), (30; 1), (32; 1), (36; 1), (3; 1), (4; 1), (2; 1), (27; 1), (26; 1), (25; 3), (20; 1), (18; 1), (11; 1), (34; 1), (19; 1), (35; 1), (9; 1), (10; 1), (12; 1), (15; 1), (16; 1), (1; 1)

From Table 3, it is observed that the result satisfies the time limit and cost limit for travel. It is also observed that total travel time is increased when the number of cities is increased, as the time matrix is randomly generated for all three instances in a same range of numbers. We have also presented the output result or tour for which the result is given in Table 4. However, only the results of the redefined ftv33 and ftv35 are presented in Table Table 4, as their size is small. In Table 4, each pair (x, y) indicates that from the x-th city, the y-th type of conveyance has been used for travel.

3.3 Experiment with a given small sized data set

Here, we have presented the results of a 6-city multi-conveyance where the input cost and time matrix for three types of conveyances are randomly generated and given in Table 5 and Table 6, respectively. The output tour cost and time are given in Table Table 7. This is to well comprehend the problem with paper and pen. The time limit for the tour is 45 units. The number of ants is 10, and the number of iterations is 100. The number of ants and iterations are chosen by random experiments. The parameters of the ACO is as same as in previous subsection.

Table 5. Input cost matrixfor 6 city multi-conveyance TSP

i/j	1	2	3	4	5	6
1	8.34, 6.87, 6.15	9.97, 9.65, 8.96	8.30, 8.31, 9.37	4.21, 9.36, 8.22	9.21, 7.28, 7.86	5.90, 4.21, 5.14
2	8.83, 9.34, 8.37	4.50, 9.72, 8.54	5.94, 7.22, 7.23	8.22, 9.58, 9.86	8.97, 8.66, 7.44	7.93, 7.44, 4.19
3	5.15, 4.04, 6.02	5.33, 7.53, 6.53	7.93, 6.46, 6.15	5.75, 9.02, 6.24	8.40, 4.32, 9.99	7.89, 6.90, 8.84
4	6.71, 7.60, 5.49	9.93, 8.21, 5.17	5.20, 6.75, 7.71	6.83, 7.73, 7.23	9.33, 4.94, 7.07	9.25, 6.60, 9.21
5	8.19, 7.34, 6.86	9.17, 8.13, 6.41	6.56, 7.70, 8.54	6.21, 8.15, 6.55	8.52, 4.83, 6.54	5.16, 5.17, 5.78
6	8.21, 5.90, 8.03	8.99, 9.67, 5.88	5.33, 4.77, 4.97	5.52, 4.14, 4.92	4.11, 8.72, 9.43	6.00, 9.24, 6.23

Table 6. Inputtime matrix for 6 city multi-conveyance TSP

i/j	1	2	3	4	5	6
1	10.85, 8.86, 9.82	8.74, 8.56, 9.42	8.79, 9.90, 10.08	10.24, 8.29, 8.33	9.65, 10.03, 7.15	10.37, 8.15, 7.42
2	8.48, 8.40, 7.02	10.36, 10.86, 8.50	7.47, 7.33, 10.72	8.22, 9.69, 8.54	7.39, 9.05, 10.94	7.21, 8.40, 7.60
3	8.83, 8.15, 10.01	10.78, 9.02, 7.12	9.50, 9.15, 9.19	7.08, 9.38, 7.08	8.67, 10.75, 10.60	8.68, 8.24, 9.47
4	9.08, 9.22, 10.19	8.94, 7.37, 8.37	9.32, 10.18, 10.19	8.17, 7.15, 7.72	7.81, 9.54, 8.09	7.57, 10.38, 8.66
5	10.57, 8.56, 7.30	10.16, 8.02, 8.69	10.33, 10.73, 7.68	9.22, 8.74, 9.20	8.12, 10.98, 9.75	8.66, 8.14, 7.42
6	10.14, 8.05, 8.25	10.02, 8.28, 9.23	9.14, 8.80, 7.69	9.04, 9.98, 9.60	10.83, 8.56, 7.81	7.64, 10.33, 7.28

Table 7. Result tour for 6-city multi-conveyance problem

Obtained tour	(1; 1), (4; 3), (2; 3), (6; 1), (5; 1), (3; 1)	Cost 28.26	Time 41.95

Each pair (x, y) in Table 7 indicates that from the x-th city, the y-th type of conveyance is used. In the input cost and time matrix, each i-th city to j-th city consists of three values each for three types of conveyances.

Table 7 presents the results of six cities' problems. It is observed that the result meets the cost and time bounds. This type of result can help the readers to understand and take the idea of how a real-life problem can also be solved by this TSP model.

4 Conclusion

In this paper, we have presented an ACO-based approach to solve a multi-conveyance TSP. This is a new version of TSP where there is a different conveyance facility to travel from city to city, and the total travel cost and time of tour are fixed. To the best of our knowledge, this is a new variant of TSP where time and cost limits are also fixed with different conveyance facilities. A novel ACO-based approach has been used to solve the TSP. A new operation "tuning solution" has been adopted for ACO to recover better neighbour solutions of each path. This is a unique feature of the ACO, which is one of the contributions of this research. To check the efficiency of the proposed ACO, a set of benchmark instances from TSPLIB has been considered. The results of benchmark instances are able to show that the proposed ACO is an efficient algorithm for TSP.

Our future aim is to implement a multi-objective TSP. Next, our other future plan is to solve the probabilistic TSP. Further we want to solve a random fuzzy type-2 TSP by a bee colony optimization algorithm. In the future, we also want to solve a multi-depot multi-conveyance TSP with a bat algorithm. Later on, we also want to focus on precedence constraints multiple-conveyance TSP in a fuzzy random environment.

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