Solving Capacitated Vehicle Routing Problem (CVRP) Using Tabu Search Algorithm (TSA)

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Abstract

This paper investigates the capacitated vehicle routing problem (CVRP) as it is one of the numerous issues that have no impeccable solutions yet. Numerous scientists in the recent couple of decades have set up various explores and utilized numerous strategies with various methods to deal with it. However, for all researches, finding the least cost is exceptionally complicated. In any case, they have figured out how to think of rough solutions that vary in efficiencies relying upon the search space. Furthermore, tabu search (TS) is utilized to resolve this issue as it is fit for solving numerous complicated issues. The algorithm has been adjusted to resolve the exploration issue, where its methodology is not quite the same as the normal algorithm. The structure of the algorithm is planned with the goal that the program does not require a substantial database to store the data, which accelerates the usage of the program execution to acquire the solution. The algorithm has demonstrated its accomplishment in resolving the issue and finds a most limited route.

Keywords: Tabu Search algorithm, Capacitated Vehicle Routing Problem, Meta-Heuristic

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Introduction

Vehicle routing problem turns into a region for exploring since it was examined by Dantzing and Ramser in 1959 [1]. An average vehicle routing problem can be portrayed as the issue of outlining minimum cost courses from one area to an arrangement of topographically scattered focuses (urban areas, stores, distribution centers, schools, colleges, clients and so forth) [2].

Traditional vehicle routing problem is outlined as follows: A set of vehicles (for conveyance of goods) begins from one area and visits a gathering of scattered urban communities or clients and come back to a similar area with less separation and expenses on the conditions [3]:

• Every city is gone by one vehicle just once inside an individual route.
• The limit of every vehicle is sufficient for all urban communities incorporated into the route.
• Routes start and end at a similar area.

The quantity of vehicles should be not as much as what can be proposed for routes and also the quantity of routes is to be not as much as what can be given to cover all urban communities. Static Vehicle Routing Problem (SVRP) implies that all the data on the route is known ahead of time before beginning and does not change after the route started. The issue will be dynamic if any limitation is forced, similar to time, vehicle limit or different factors [4].

Vehicle Routing Problem (VRP)

VRP gets a great deal of consideration and turns into a concentration of various researches, in light of the fact that it is fundamentally the same as the Traveling Salesman Problem (TSP), which is considered as the base of VRP. In any case, there is a major contrast between them, not at all like the Traveling Salesman Problem; VRP is a multi-constrained optimization issue.

Conventional VRP plans to decide the most minimal cost of a route for a vehicle beginning from focal warehouse to serve an arrangement of clients and return back to a similar focal warehouse. The VRP has numerous limitations, for example, vehicle limit, time window, multi-warehouses and others, which gives it more complicated settlement space [5]. Figure (1) clarifies the process.
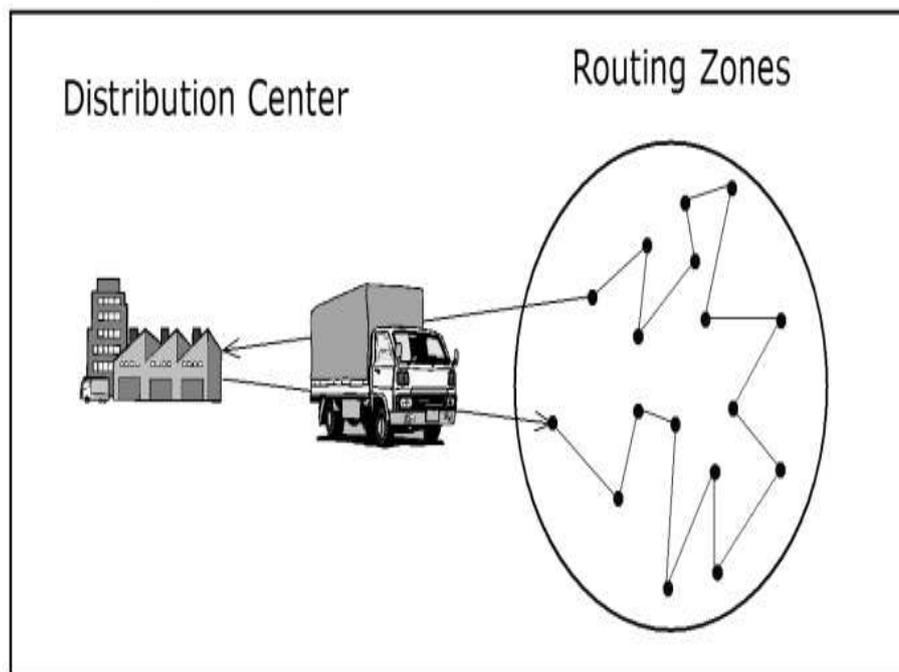

Figure (1): VRP process [27]

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The Capacitated Vehicle Routing Problem (CVRP)

CVRP is the fundamental adaptation of the VRP, where the vehicles have constrained capacity. In the traditional version of the CVRP, all data about client requests is known ahead of time. The vehicle fleet is identical and there is just a single depot and each request can't be isolated or served utilizing at least two vehicles. The goal is to reduce travel cost. The CVRP is the same as the VRP, yet on the condition that the aggregate of all client requests for each route does not surpass the vehicle capacity. The VRP is viewed as dynamic if the limit of every vehicle is not constrained to mull over any new request [6]

Objectives of VRP

The applications in VRP are produced by the demanded objectives. These objectives are to limit the conveyance, vehicle expenditure, to optimize the figure of vehicles and drivers, to optimize the invested energy amid the conveyance period, to reduce the aggregate traveled range. The applications might be created by one of these exhibited objectives or some of these introduced objectives by joining them and furthermore considering their inconsistencies. At that point the VRP problem transforms into a multi-target choice problem.

VRP considers giving advantageous administration dispersion for client requests between the characterized focuses on the outline. Application regions create as indicated by the requests of clients. Essential application fields are fuel and diesel conveyance, the course of action of the officers in a combat zone, flights of planes, conveyance of nourishment and refreshment to the restaurant, conveyance of cash to the bank ATMs and money machines, understudy and laborer administrations, conveyance of parcels that are acquired by shopping over web, trash gathering, and transporting [7].

CVRP Model

Capacitated Vehicle Routing Problem (CVRP) was realized by [8] and [9] as a set of n clients served from the normal station or distribution center, for a non negative q_i client request by N number of vehicles of having capacity of Q and separation or cost of C_{ij} between two nodes of i and j by vehicle k. The goal of CVRP is to decide ideal route plan which minimizes the distance or cost with the accompanying requirements:
• Each client is served precisely once by precisely one vehicle
• Each vehicle begins and finishes its route at the depot
• The aggregate length of each route should not surpass the limitation
• The aggregate request of any route should not surpass the capacity of the vehicle

Literature Review

There were two methods of research in order to tackle the VRP. One included accurate strategies of finding the ideal solution by registering every single conceivable solution and the other was heuristic or meta-heuristic methodologies, which played out a generally constrained investigation of the search space and ordinarily created great quality solutions with unassuming processing times. Accurate techniques can be ordered into the accompanying classes: dynamic programming, set apportioning, branch-and-bound, and branch-and-cut. As of not long ago, accurate strategies for the CVRP have been overwhelmed by branch-and-cut. Truly outstanding branch-and-cut algorithms were created by Lysgaard et al. [9].

Late research came about demonstrated that branch-and-cut-and-value algorithms were additionally encouraging approaches for the CVRP as Fukasawa et al. [10] appeared. Heuristic strategies can be extensively grouped into two primary classes: established heuristics grew for the most part in the vicinity of 1960 and 1990, and meta-heuristics effectively investigated from the 1990's. The Clarke and Wright sparing algorithm [11] was a delegate traditional heuristic approach connected to issues where the quantity of vehicles was not settled.

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A few improvements to the Clarke and Wright algorithm were proposed [12, 13], which went for decreasing calculation time and memory requirements. Addition heuristic was another notable established strategy; Mole, and Jameson [14] extended one route at once and Christofides et al. [15] connected, in turn, a successive and a parallel route development system.

Tabu Search Algorithm

Tabu search algorithm has a place with meta-heuristic technique under heuristic strategies. Tabu search is produced by [16] for proposing an improved solution for VRP. The fundamental thought of tabu search algorithm is keeping from redundancies and disallowing or rebuffing the redundancy in the following stage. The tabu technique was halfway spurred by the perception that human conduct seems to work with an irregular component that prompts conflicting conduct given comparative conditions.

The tabu technique works thusly with the exemption that new courses are not picked arbitrarily. Rather the tabu search continues as indicated by the supposition that there is no reason for tolerating another (poor) solutions unless it is bypass a route already explored [17]. This guarantees new areas of problems solutions space will be researched in with the aim of avoiding local minima and at last finding the coveted solution. For this situation, tabu search encourages to use memory utilization to bypass an endless loop.

The tabu search starts by progress to local minima. To abstain from remembering the means utilized the strategy records later moves in at least one tabu lists [18]. The first plan of the list was not to keep a past move from being rehashed, but instead to safeguard it was not turned around [19]. The tabu lists are verifiable in nature and shape the tabu search memory. The part of the memory can change as the algorithm continues [20]. The following figure shows the flowchart of standard tabu search algorithm [21].
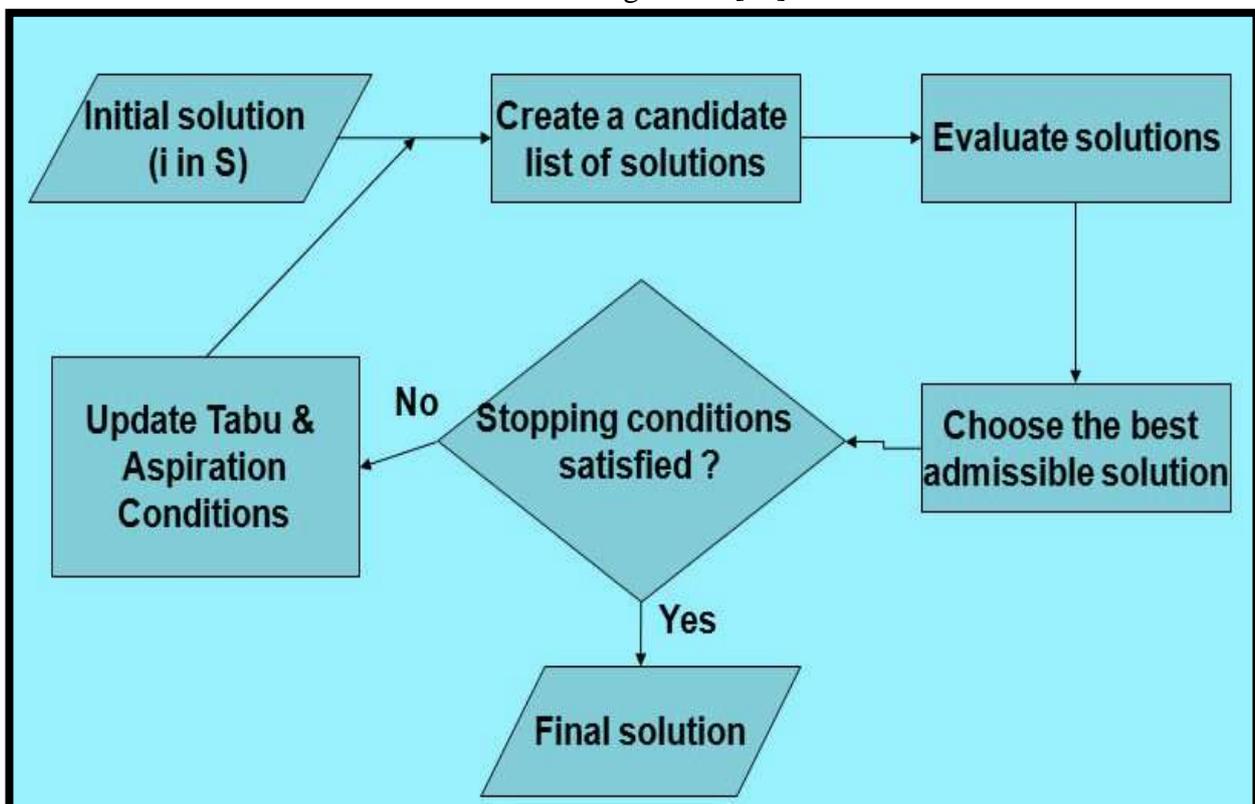

Figure (2): Flowchart of standard tabu search algorithm [21

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Tabu list keeps the states that ought not to be taken at the search. The space of the tabu list influences the outcome. Tabu smash criterions are where the tabu vanishes. Most broad tabu pulverize basis is getting nearer result with the created solution than more outdated solution, thus, the tabu is obliterated. The viability of tabu search algorithm increments with using this criterion.

Tabu search proceeds with its search till giving at least one interception check. Some of these rules are: the picked neighbor solution has no neighbor, to achieve a distinct number of resumption, to reach a distinct estimation of a solution, the algorithm gets cohesive and it does not output better outcome [22].

The pseudo code of the tabu search algorithm which presented in [26] as follows:

```
1: s ← s0
2: sBest ← s
3: tabuList ← null
4: while (not stoppingCondition())
5: candidateList ← null
6: for (sCandidate in sNeighborhood)
7: if (not containsTabuElements(sCandidate, tabuList))
8: candidateList ← candidateList + sCandidate
9: end
10: end
11: sCandidate ← LocateBestCandidate(candidateList)
12: if (fitness (sCandidate) > fitness (sBest))
13: sBest ← sCandidate
14: tabuList ← featureDifferences(sCandidate, sBest)
15: while (size (tabuList) > maxTabuListSize)
16: ExpireFeatures(tabuList)
17: end
18: end
19: end
20: return (sBest)
```

Figure (3): Pseudo code of tabu search algorithm [26]

HeuristicLab (Used Tool)

HeuristicLab was developed as a software for heuristic and developmental algorithms, created by individuals from the Heuristic and Evolutionary Algorithm Laboratory (HEAL) at University of Applied Sciences Upper Austria, Campus Hagenberg. HeuristicLab has a solid concentrate on giving a graphical user interface so clients are not required to have thorough programming aptitudes to modify and expand the algorithms for a specific issue. In

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HeuristicLab, algorithms work as administrator diagrams and changing or reworking, administrators should be possible by intuitive without really composing code.

The product in this way tries to move algorithm improvement capacity from the product architect to the client and expert. Designers can even now expand the usefulness on code level and can utilize HeuristicLab's module instrument that enables them to coordinate custom algorithms, arrangement portrayals or optimization problems [23, 24].

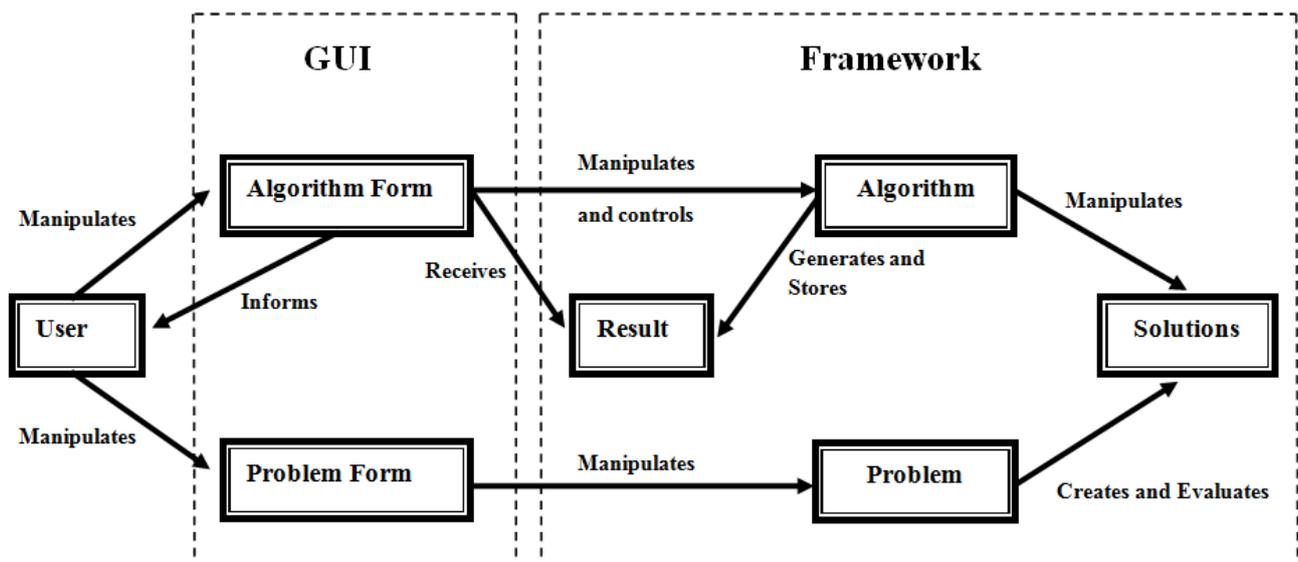The following figure illustrates the interaction of HeuristicLab classes.

Figure (4): Interaction of HeuristicLab classes [23]

Experimental Results

The tabu search algorithm is examined on Christofides and Eilon benchmark dataset [25]. The file name contains data about the quantity of nodes in the datum and the minimal number of vehicles expected to tackle the problem. For instance, E-n101-k14 shows that this issue is of class E, the quantity of nodes including the depot is 101, and the minimal number of vehicles required is 14. Tests are carried out on Dell computer (INSPIRON), and Windows 7 Ultimate 64-bit as operating system with a Pentium Dual Processor 2.20 GHz and 3072 MB RAM.

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Table (1): Experimental results of the Christofides and Eilon benchmark dataset

Instance	Best Known	Vehicle Utilization	Overload	Execution Time H.M.S
E-n101-k14	1122	14	1	00.04.26
E-n101-k8	835	8	3	00.02.54
E-n13-k4	247	4	0	00.00.06
E-n22-k4	375	4	0	00.00.11
E-n23-k3	569	3	0	00.00.09
E-n30-k3	506	4	0	00.00.14
E-n31-k7	427	7	0	00.00.28
E-n33-k4	835	4	0	00.00.17
E-n51-k5	521	5	0	00.00.35
E-n76-k10	830	10	0	00.01.59
E-n76-k14	1021	15	0	00.03.00
E-n76-k7	662	7	0	00.01.25
E-n76-k8	756	8	0	00.01.35

Table (1) above, illustrates the outcomes. The instances of benchmark dataset have clarified in column one and the best known (shortest) distance have clarified in column two. Furthermore, the best valid solution for the vehicle utilization was illustrated in column three. In addition, the tabu percent for each instance was illustrated in column four. Finally, the best VRP solution overload and the execution time were clarified in column five and six respectively.

On the other hand, table (2) below represents the fixed parameters which have been used for the tabu search algorithm, in order to solve the capacitated vehicle routing problem.
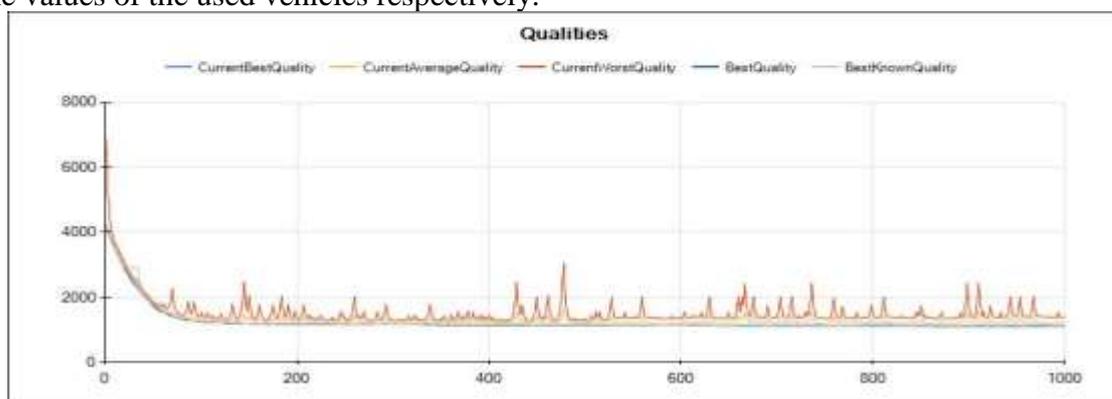
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Table (2): Fixed Parameters of TSA

Analyzer	MultiAnalyzer
MaximumIterations	1000
MoveEvaluator	PotvinCustomerRelocationMoveEvaluator
MoveGenerator	PotvinCustomerRelocationExhaustiveMoveGenerator
MoveMaker	PotvinCustomerRelocationMoveMaker
SampleSize	100
Seed	640517055
SetSeedRandomly	false
TabuChecker	PotvinCustomerRelocationTabuCriterion
TabuMaker	PotvinCustomerRelocationMoveTabuMaker
TabuTenure	6

One thing ought to be observed in table (1), instances with the little size besides allocation manner at random, tabu search algorithm leads to preferable outcomes particularly when the vehicles have average capacity, so, the execution time will be shorter. On the other hand, increasing the size of instances results in more time in order to execution, and there will be a possibility that there will be an overload. Finally, the tabu percent will be increasing in the instances which have little size.

Figures of Instances (Samples)

The following figures show the qualities of the solutions, the total distances of the solutions and the values of the used vehicles respectively.
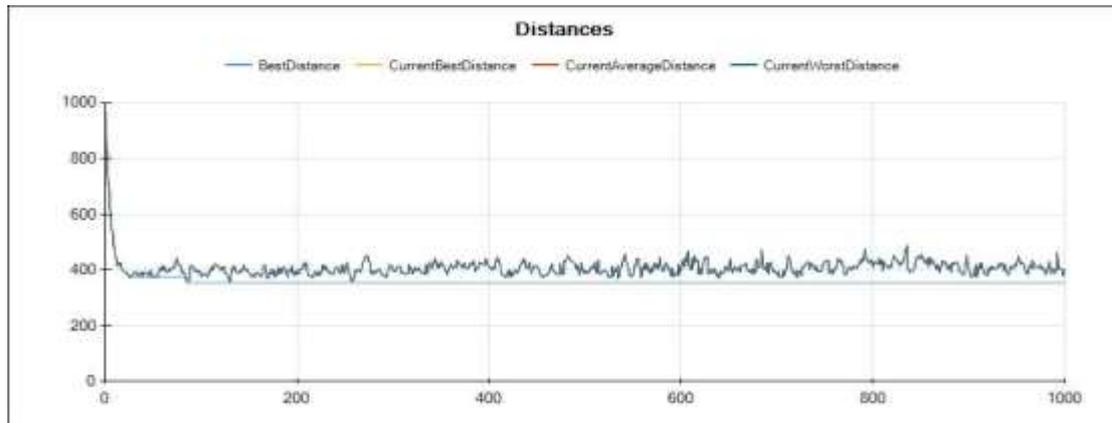

Figure (5): Qualities

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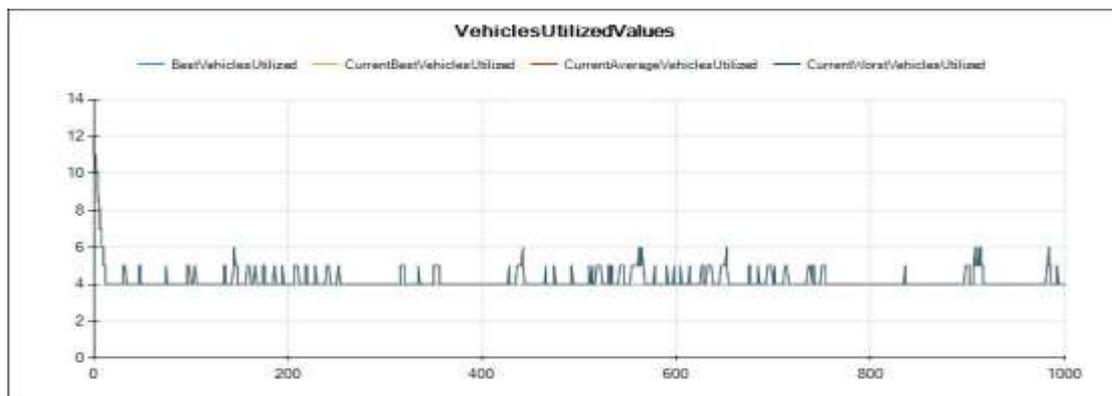**Figure (6): Distances**

Figure (7): Values of Used Vehicles

Conclusion

Capacitated vehicle routing problem (CVRP) cannot be resolved in polynomial time due to its belonging to nondeterministic polynomial-time (NP) hard problems. In this paper, Tabu Search Algorithm (TSA) is suggested for the capacitated vehicle routing problem. The experiments were tested on well Christofides and Eilon benchmark dataset. TSA has demonstrated its ability to expand rise quality settlements to the (CVRP) in feasible calculation time in an effective way. Moreover, TSA is a deterministic algorithm, so every one of the outcomes is completely reproducible. TSA has proved that instances with the little size besides allocation manner at random, it leads to preferable outcomes particularly while the vehicles have average capacity, so, the execution time will be shorter. On the other hand, TSA has used fixed parameters as clarified in table (2). In the future, it would be a good idea to expand the algorithm to more complicated issues such as heterogeneous fleet of vehicles and time window.

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