Improved Nature Inspired Intelligence Techniques for Shortest Path Routing in Network Problems

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***Abstract*:** One of the central problems of supply chain management is the coordination of product and material flows between locations. A typical problem involves bringing products located at a central facility to geographically dispersed facilities at minimum cost. One basic and well-known problem in transportation is the vehicle scheduling and routing. A vehicle scheduling system should output a set of instructions telling drivers what to deliver, when and where. An "efficient" solution is one that enables goods to be delivered when and where required at least cost, subject to legal and political constraints. The legal constraints relate to hours of work, speed limits, vehicle construction and use regulations, and restrictions for unloading, and so on. With the growing of sales by Internet, this problem is gaining enormous importance, since the delivery times are usually very short, the customers can be dispersed in a region, every day there is a different set of customers and also with very short time-windows to deliver the product. This proposed work presents a decision support system based on Artificial Intelligence Heuristics for a single- mode Routing problem.

Keywords: TSP, mTSP, Vehicle Routing Problem, SWA, BMT, Simulated Anealing.

1 Introduction

Traveling salesman problem is considered as puzzles by academicians and engineers. One such "Vehicle routing problem" is a typical problem faced in the distribution of the supply chain network. There are various locations (customer ends) to be met with given suppliers of particular processed industry products or item or group of items. The issue is how to route the vehicle so that it visits each location with a view to minimizing the total cost involved. Many stations need to be traveled by sales executives, and he supposed to travel back to the same station. While solving the modal it is necessary to develop the route keep in a target that the total distance covered by the sales executive is to be optimized, i.e., maximum extent minimized the cost involved.

2 Multiple – traveling salesman problem (mTSP):

The mTSP can, in general, defined as follows: Given a set of nodes, let there be m salesmen located at a single depot node. Intermediate nodes are the remaining nodes (cities) to be visited. Then, the mTSP consists of finding tours for all m salesmen, whom all start and end at the depot, such that each intermediate node visits precisely once and the total distance of visiting all nodes is minimized. Although there were any researches done on TSP the research on the mTSP is limited because the mTSP is very difficult when compared to TSP. mTSP requires the determination that which cities to assign to each salesperson.

In the m-TSP problem, "the m-salesman has to cover the given cities, and exactly one salesman must visit each city. The characteristics of the salesmen are that they begin and end at the depot node." The Vehicle Routing Problem (VRP) is "the m-TSP, where demand associated with each city or customer and, each vehicle has a certain capacity. Moreover, in VRP also the number of vehicles, m, is often considered as a minimization criterion in addition to total traveled distance."The problem of finding least cost routes from one depot to a set of geographically scattered points (cities, stores, warehouses, schools, customers etc.)" is called as Vehicle routing problem .The specifications of the routes are that "each station is visited only once by exactly one vehicle, all routes start and end at the depot, and the total demands of all points on one particular route cannot exceed the capacity of the vehicle engaged."

"Vehicle routing problem" is a space model task. The problem is defined "with time windows. The service to the customers can be done during certain hours of the day, such as office hours or the hours before the opening of a shop". Concerning this as a certain case, "A warehouse may only accept deliveries between 8:00 AM and 5:00 PM. Therefore, much attention has been given to the Vehicle Routing Problem with Time Windows (VRPTW)."The proposed time windows considered as hard or soft. Concerning hard time window situation is defined as "if a vehicle arrives too early at a customer, it is permitted to wait until the customer is ready to begin service." However, a vehicle is not permitted to arrive at a customer after the latest time to begin service. Whereas, in the soft time window case the time windows can be violated at a cost.

Applications like "garbage collection, mail delivery, snow clearing, meter reading, school bus routing, police patrols etc.,"Arc Routing Problems (ARPs), adopted for a "least cost traversal of all arcs of a graph, subject to constraints." whereas an in-vehicle routing problem, the "pick-up and delivery problems each transportation request specifies both the stations where the load is to be picked up and the stations where it is to be delivered. Each load has to be transported by one vehicle from its set of the initial station to its set of destinations without any transshipment at other locations". Unbalanced routing may yield to the under or over utilization of assets and facilities. It may lead further deteriorate the customer service. The logistics manager needs a decision support system (DSS) for operational decision-making of balanced routing. This part of the research is to develop a "decision support system" based on a heuristic for a balanced routing problem to run the business effectively in a dynamic system of the supply chain. This above explained problem is referred to as "balanced multiple traveling salesman problem (BMT)," it is an extended version of multiple traveling salesman problem (mTSP). The heuristic is developed as earlier suggested by "Ganesh & Narendran (2007)". The main aim of this paper is to "Transform the mTSP to TSP, and this is done using a popular clustering algorithm." "Cluster initialization is done by a simple technique which results in reducing the computational time".

3 Problem Definition

Chandran et al. (2006), the balanced multiple traveling salesman problems is a problem which was developed as "a heuristic based on balanced load clustering and cluster length approximation algorithm.""Traveling Salesman Problem (TSP)" is highlighted model optimization case in "combinatorial optimization." TSP is "a classic routed problem in which a hypothetical salesman must find the most efficient sequence of destinations in his territory, stopping only once at each, and ending up at the initial starting location." The combinatorial complexity of the traveling salesman problem, heuristic solution approaches are almost always adopted in practice.

Most applications originate in the real world problems like vehicle routing, clustering a data array, job-shop scheduling or computer wiring (Laporte & Osman 1995; Lawler et al. 1985). Given a set of cities, with m number of salesmen located at a single location called "depot city" and intermediate cities as remaining cities that are to be visited. The constraints of movement are the same as found in the TSP in "that each intermediate city visited exactly once and the total cost of visiting all cities are minimized (Bektas 2006)".Considered balanced multiple traveling salesman problems, the distance between the vehicles are balanced to improve the asset utilization and customer service level (Okonjo-Adigwe 1988; Chandran et al. 2006). "All the salesmen have to start from a station and after traveling through different cities, all are supposed to return to the starting station, keeping that no capacity constraints and no cost constraints. All the stations must be visited by any one of the salesmen, and each salesman has to visit a particular station exactly once".

4 Decision Support System Based on Heuristic — A Case Study

We develop a DSS based on three-stage heuristic to solve BMT. In the first stage, we cluster the nodes based on a clustering approach. In the second phase, we used shrink wrap algorithm proposed by Ganesh & Narendran (2007) to form the initial tour. In the third stage, we develop a simulated annealing (SA) approach to improve and balance the tour. The Flowchart representing the heuristic is given in Figure 4.1.

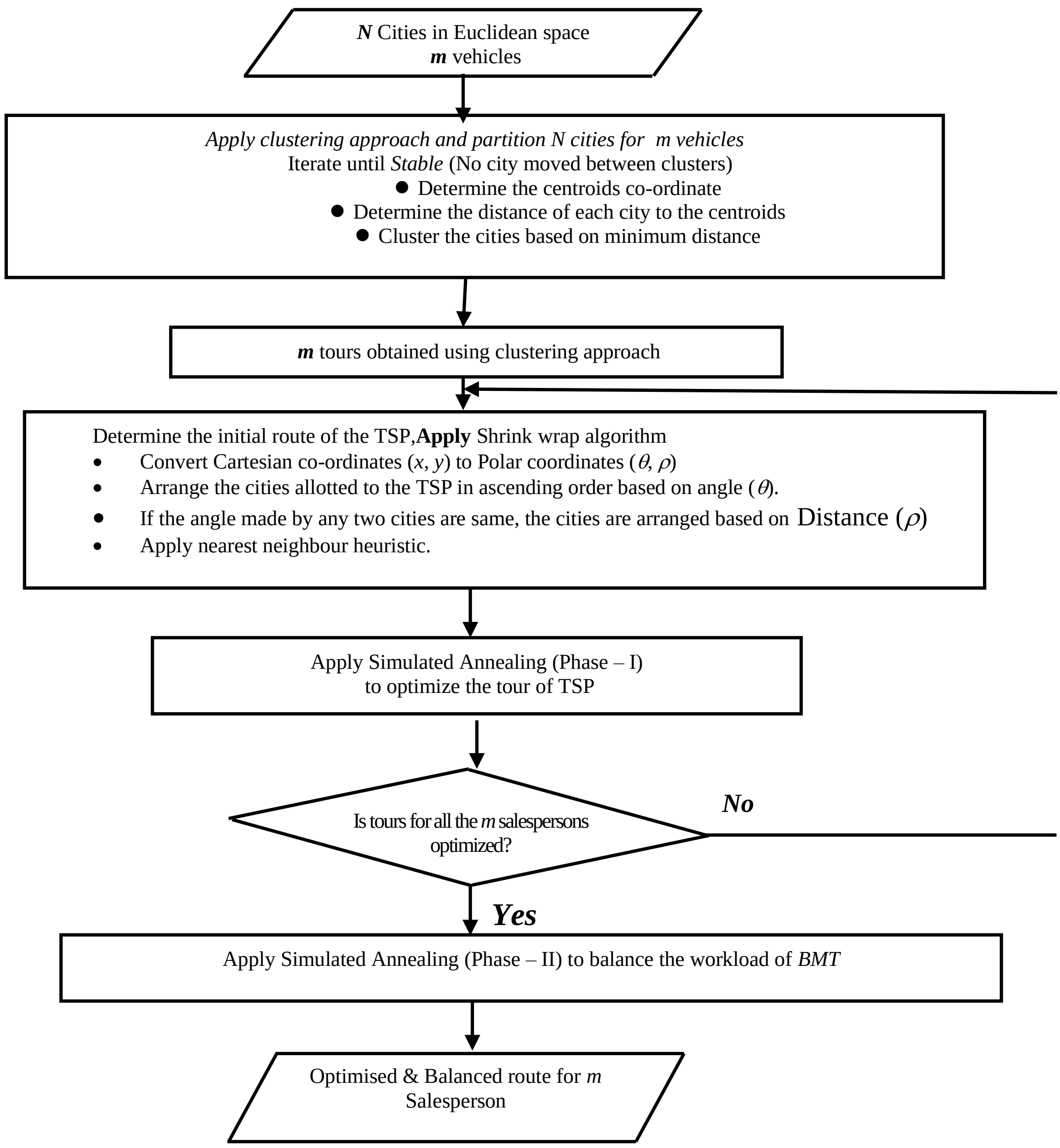

Fig .4.1. DSS Based on Heuristic for BMT

DSS based on heuristic is applied for a school van routing case study. The details of the heuristic are explained with a case study. There are school 6 vans which needs to route through 60 places to pick-up the kids for school. The objective is found the balanced routing with minimal cost.

4.1 First Phase of Heuristic

It is the fact that the sum of factorials is much smaller than the factorial of the sum which is a concept of clustering. It provides a computational advantage for the selected case under study. Anderberg 1973, "for N cities, the search space is a function of N!. Thus the computing time, which is proportional to the search space, is also a function of N!. When N is a large number, the computing time is very high. If N cities divided into P clusters, the average number of cities in each cluster in N/P. "The search space for each cluster is a function of (N/P)!. The total search space for all clusters is P (N/P)!."

When "N is large, clustering saves time by several orders of magnitude, since

$$P \times \left(\frac{N}{P}\right)! \langle\langle\ N!$$

for large N and P."

4.2.1 Clustering Approach:

Different steps of the "clustering approach" are as follows:

Step 1:"Choose K initial cluster centers $Z_1, Z_2, \ldots, Z_k$ from the 'n' points $\{X_1, X_2, \ldots, X_n\}$"

Step 2:"Assign point X_i, $i = 1, 2, \ldots, n$ to cluster C_j, $j\in \{1, 2, \ldots, K\}$iff $\|X_i - Z_j\| < \|X_i - Z_p\|$, $p = 1, 2, \ldots, K$, and $j \# p$

Ties are resolved arbitrarily"

Step 3: "Compute new cluster centers $Z_1^*, Z_2^*, \ldots, Z_k^*$ as follows":

$$\text{“ } Z_i^* = \frac{1}{n_i} \sum_{X_j = C_i} X_j, \qquad i = 1, 2, \ldots, K, \text{”.}$$

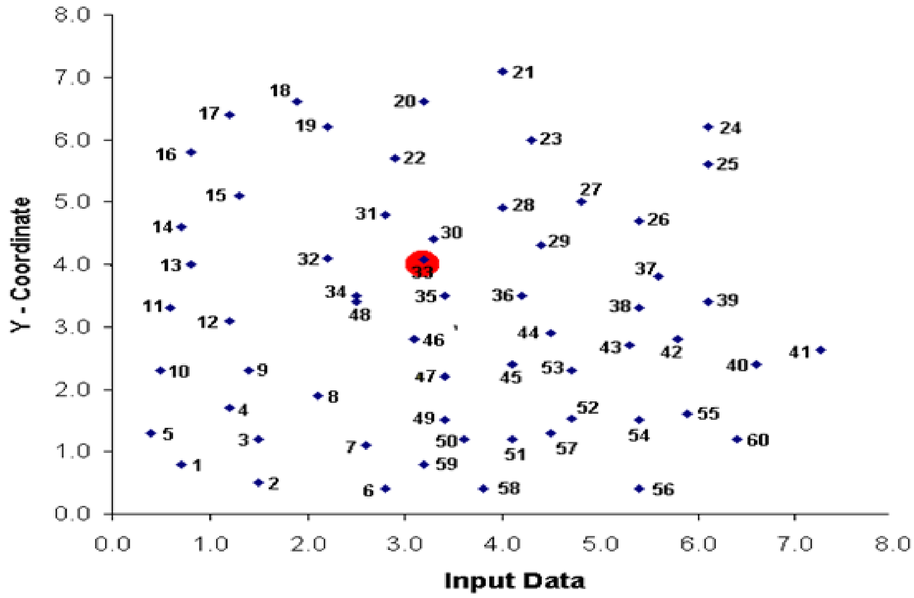

Fig.4.2. Input Data for the Case Study

"n_i" "is the number of elements belonging to cluster""C_i."

"Step 4: If""$Z_i^* = Z_i$, $i = 1, 2 \ldots K$*"* then terminate.

Otherwise repeat from step2.

The input data for a case study is shown in Figure 5.2.

The proposed algorithm is converged type. The number of iterations required is unknown. The clustering approach is used. The convergence is not assured to yield the best solution. The initial set of clusters bound to generate quality of end solution. Hence the following methodology is adapted to initialize the centroids. By arranging the cities based on the distance calculated using the Euclidean distance formula,

$$\sqrt{[(x_1 - x_2)^2 + (y_1 - y_2)^2]}$$

We find the cities 33, 30, 31 are very close to the depot and the cities 56, 60, 41 are farthest from the depot considered. In the formulae, suffix 1 & 2 represent the cities between which distances are to be calculated. Here we have considered the depot itself as an initial centroid. The initial cluster centroids are given in the Table 4.1.

Table.4.1. Initial Cluster Centroids

Cluster No	X-coordinate	Y-coordinate
1	3.1	4.2
2	3.3	4.5
3	2.8	4.8
4	5.4	0.4
5	6.4	1.2
6	7.7	2.6

By applying the clustering approach, mTSP is transformed in to TSPs and the results are shown in Table 4.2 and Figure 4.3.

Table.4.2. Final Results of Clustering Approach

Vans	Cities Allotted	No. of cities
1	1, 3, 4, 5, 8, 9, 10, 11, 12, 13, 34, 46, 48	13
2	21, 23, 24, 25, 26, 27, 28, 29, 30, 35, 36	11
3	14, 15, 16, 17, 18, 19, 20, 22, 31, 32	10
4	2, 6, 7, 47, 49, 50, 51, 58, 59	9
5	43, 44, 45, 52, 53, 54, 55, 56, 57, 60	10
6	37, 38, 39, 40, 41, 42	6

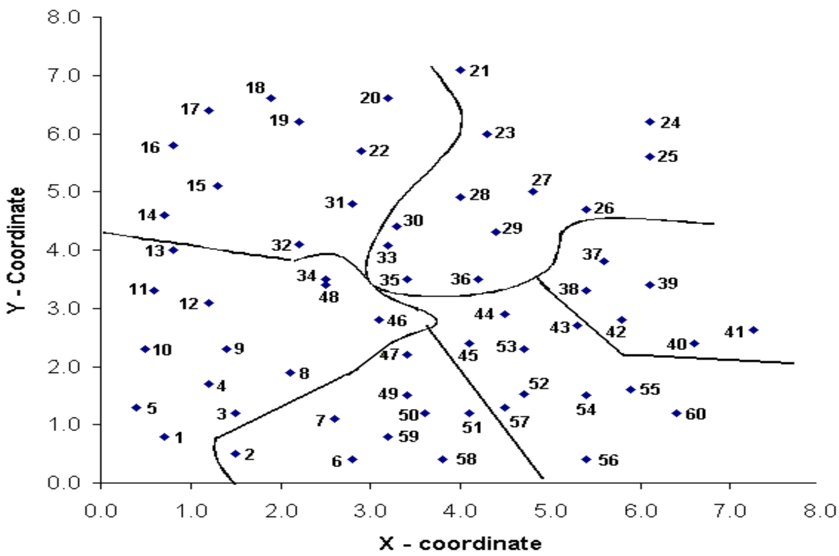

Fig.4.3. Output of Clustering Approach

4.3 Second Phase of Heuristic - Shrink Wrap Algorithm

From the cluster selected, the nodes are oriented “along a path using the Shrink-Wrap Algorithm” (Lawler et al. 1985, Ganesh & Narendran 2007). The polar coordinates are adapted to map the nodes. It is “sorted by angle, then by distance (θ first, then ρ) and arranged in increasing order which yields the path within each cluster.” Different steps indicated are shown in Figure 4.4. So, the cluster approach is used for generating clusters, and then “shrink-wrap algorithm” is used to optimize the clusters and finally, the cluster is unwrapped using nearest neighbor heuristic. The results given in Table 4.3 and the output are shown in Figure 4.5.

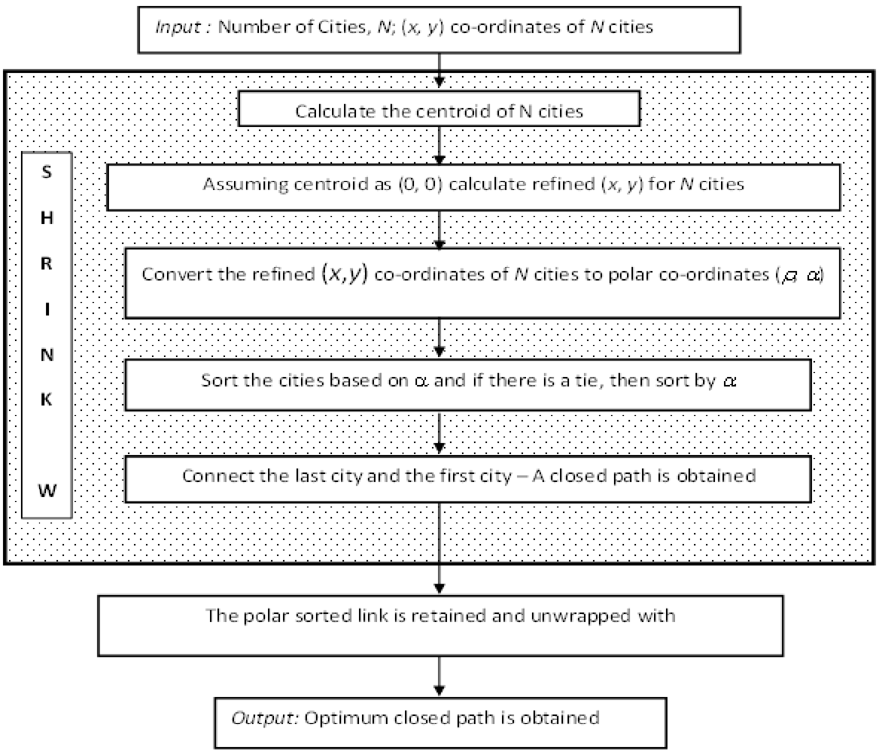

Fig.4.4. Second Phase - Shrink wrap algorithm

Table.4.3. "Results of Shrink Wrap Algorithm" Approach

Vans	"Route generated"	"Distance to travel"
1	33–48–34–46–8–3–9–4–1–5–10–11–13–12–33	13.4058
2	33–30–28–21–23–24–25–27–26–29–36–35–33	12.4839
3	33–31–32–14–15–16–17–18–19–20–22–33	10.3033
4	33–47–49–50–51–58–59–6–2–7–33	11.4210
5	33–44–43–55–60–54–56–57–52–45–53–33	12.5020
6	33–38–37–39–41–40–42–33	10.4913

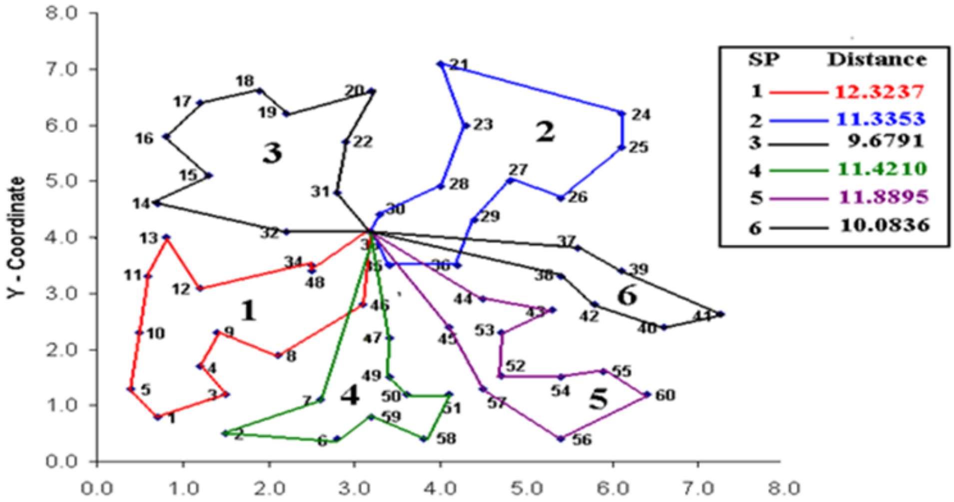

Fig.4.5. Routing Results of Shrink-Wrap Algorithm

4.4 Third Phase – Simulated Annealing for Improving and Balancing the Route

The cities sequence obtained using the cluster analysis heuristic is considered as the chromosome for SA. The generated sequences are random. Simulated Annealing is applied to obtain a better solution in minimum computation time. A new possible solution is generated with the "current state by using a single insertion neighborhood creation scheme by creating 2(n-1)" neighborhoods.

Neighbor solutions are generated randomly with the restriction on the number of vehicles and the capacity restriction of vehicles. The number of neighborhood "common formula used is 2 (n-1)". The objective function is chosen from the best neighborhoods. The flow chart for SA is shown in Figure 4.6. The output arrived by the shrink wrap algorithm.

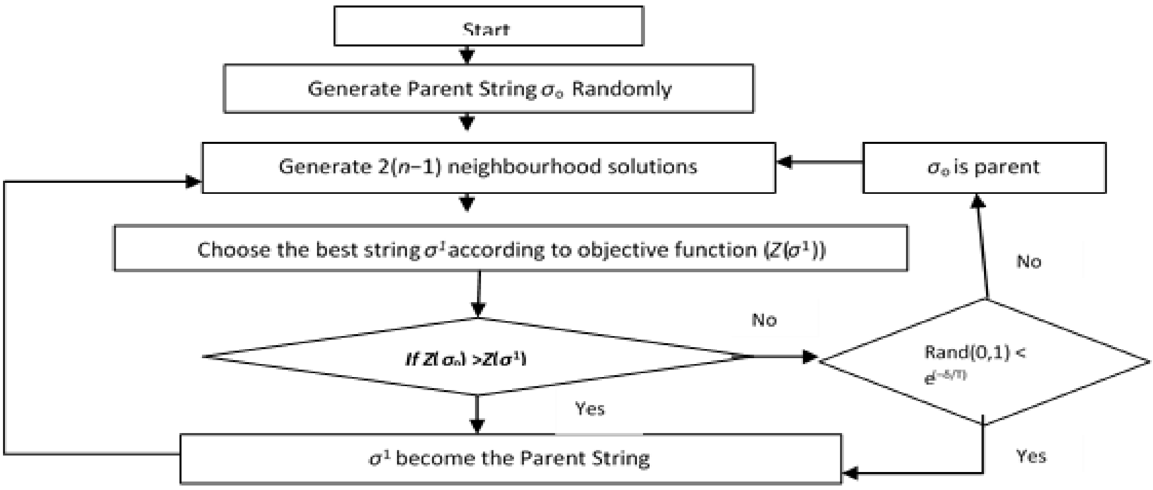

Fig.4.6. Flow chart for SA

It is improved by using meta-heuristic-simulated annealing. The algorithm for simulated annealing and the results (Table 4.4) “obtained in this stage of the heuristic is given in Figure 4.7”.

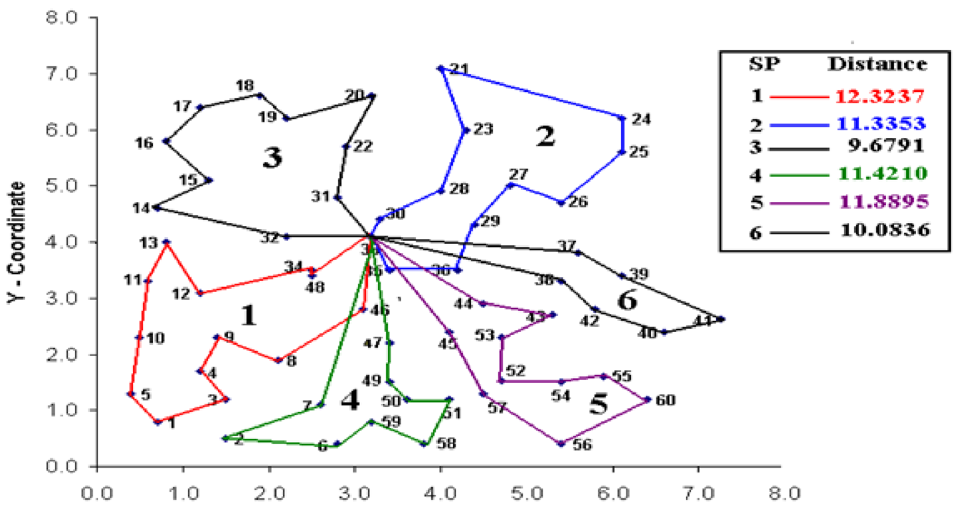

Fig.4.7. Improved Solutions by SA

Table.4.4 Results of simulated annealing

Vans	Route generated	Distance to travel
1	33–46–8–9–4–3–1–5–10–11–13–12–34–48–33	12.3237
2	33–30–28–23–21–24–25–26–27–29–36–35–33	11.3353
3	33–32–14–15–16–17–18–19–20–22–31–33	9.6791

4	33–47–49–50–51–58–59–6–2–7–33	11.4210
5	33–44–43–54–55–60–56–57–52–53–45–33	11.3932
6	33–37–39–41–40–42–38–33	10.0836

4.5 Balancing the Route using SA

The optimized route obtained from the route improvement heuristic gives a path for the van to travel. However, it is noticed that the distance traveled by the van were not equal. Since this may decrease the morale of the employees, any employee-oriented organization would like to balance their workload as far as possible. These differences in workload can be minimized by minimizing the standard deviation of the output. Standard deviation indicates the variability of data around its mean. The higher is the standard deviation, and the greater is the variability in data. So, the objective of balancing heuristic is to minimize the standard deviation up-to-the lowest possible value. If the standard deviation is 0, all the numbers are the same. However, in balancing the distance, this may not be possible because we may not get the exact distances for all the vans. Hence, we choose the criteria as minimizing the standard deviation up-to-the lowest possible value (may be greater than zero) (Bedeian & Mossholder 2000).

The standard deviation for this problem is given by

$$s = \sqrt{\Sigma(X - \overline{X})^2 / (n-1)}$$

where,

s = standard deviation

X = distance traveled by the van

n = number of vans.

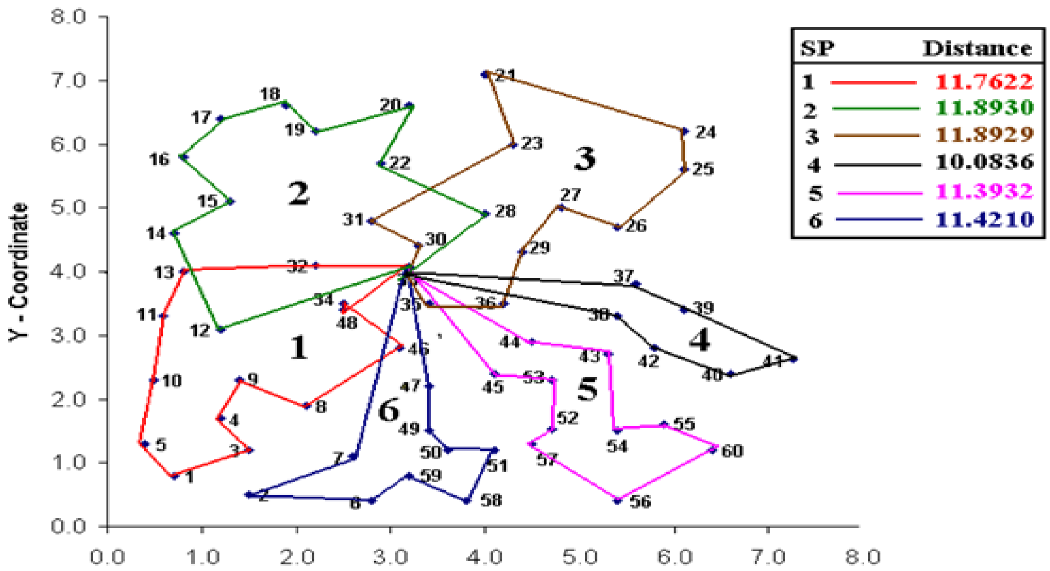

Fig.4.8. Balanced Routes by SA

Table.4.5 Results of Balancing Route of Third Phase SA

Sales Person	**Route generated**	**Distance to travel**
1	33 – 48 – 34 – 46 – 8 – 9 – 4 – 3 – 1 – 5 – 10 – 11 – 13 – 32 – 33	11.7622
2	33 – 30 – 31 – 23 – 21 – 24 – 25 – 26 – 27 – 29 – 36 – 35 – 33	11.8929
3	33 – 45 – 53 – 52 – 57 – 56 – 60 – 55 – 54 – 43 – 44 – 33	11.3932
4	33 – 47 – 49 – 50 – 51 – 58 – 59 – 6 – 2 – 7 – 33	11.4210
5	33 – 12 – 14 – 15 – 16 – 17 – 18 – 19 – 20 – 22 – 28 –33	11.8930
6	33 – 37 – 39 – 41 – 40 – 42 – 38 – 33	10.0836

Hence, by converting the standard deviation to a minimum possible value, one can balance the workload. In this work, we find the initial standard deviation is 1.065654 and converging the same using SA we find the minimum possible value is 0.470163. In this case, the distance traveled by the van shown in Table 5.5 and Figure 5.6. The sum of distances to be traveled by the six vans is 66.7322 (Optimum), and it is unbalanced. The tour, the increase in the total tour length is to be accepted to balance the tour, but as far as possible this value should be minimum.

5 Results and Discussions

In the first phase, the initial seeds for clustering approach affect the output quality of the clusters formed and this has solved by taking the nearest and farthest city locations as seeds alternatively. This approach forms a better approach when compared to random selection. If the second phase of the heuristic is skipped off, it may be noticed that achieving optimality for the van tour is difficult as the Simulated annealing (SA) is a prolonged process and it takes more time to converge. Hence, Shrink-wrap algorithm is applied to form the initial tour, and it serves as the input for SA. Since the output of SA is not be of global minimum, the third phase of the heuristic helps us to rely upon SA as it takes less burden of solving a TSP. Hence, we can conclude that the SA can be applied to improve the optimality of the tour for BMT. The balanced route travelled by the vans is shown in Figure 4.8.The total distance to be traveled by the six vans reduced from 70.6073 to 66.2359. After applying the balancing rule of the third phase of heuristic, it may be noticed that the total increase in distance is only 2.5 % and the distances are almost balanced. The results comparisons are shown in Table 5.1.

Vans	**UnOptimised Distance**	**Optimised Distance**	**Balanced Distance**
1	13.4058	12.3237	11.7622
2	12.4839	11.3353	11.8929
3	10.3033	9.6791	11.3932
4	11.4210	11.4210	11.4210
5	12.5020	11.3932	11.8930
6	10.4913	10.0836	10.0836
TOTAL	**70.6073**	**66.2359**	**68.4459**

Table.5.1. Comparison of Distances at Various Phases of Heuristic

6 Conclusion

This work proposed a workable and simple method of solving a balanced multiple traveling salesperson problem (BMT) with the issue of balancing the workload at a reasonable time. This heuristic balanced the workload with the increase in a tour length of only 2.5 %. Hence, this methodology finds direct or indirect method to solve practical applications such as reverse logistics, service logistics and many more. Most of the logistics issues have a pickup or only delivery or both pickup and delivery. This issue is addressed by imposing many constraints in solving an mTSP. For deterministic models, this heuristic is directly useful. However, for stochastic models, the research is still needed to make it useful for Decision Support system (DSS). Since Simulated Annealing takes much computational time, researchers can explore Genetic algorithm, Tabu search, and artificial neural networks may be applied for solving the BMT.

References

1. Abid Hussain,Yousaf Shad Muhammad, M. Nauman Sajid,Ijaz Hussain,Alaa Mohamd Shoukry, and Showkat Gani, “Genetic Algorithm for Traveling Salesman Problem with Modified Cycle Crossover Operator”, Hindawi Computational Intelligence and Neuroscience,pp.1-7,October 2017.
2. Ahmad Fouad El-Samak and Wesam Ashour, “Optimization of traveling salesman problem using affinity propagation clustering and genetic algorithm” , Journal of Artificial Intelligence and Soft Computing Research(JAISCR), Vol. 5, No. 4, pp. 239-245, 2015.
3. Keivan Borna and Vahid Haji Hashemi, “An improved genetic algorithm with a local optimization strategy and an extra mutation level for solving traveling salesman problem”, International Journal of Computer Science, Engineering and Information Technology (IJCSEIT), Vol. 4, No.4, August 2014.
4. Keskin, B and Uster.H, “A scatter search-based heuristic to locate capacitated transshipment points”, Computers & Operations Research, Vol.34,No.10, pp.3112–3125,2007.
5. Shinichiro Ataka and Mitsuo Gen, “Solving exclusionary side constrained logistics network by using priority-based GA”, Congress on Evolutionary Computation, IEEE,pp.4483-4488,2007.
6. Jayaraman.V and Ross.A, “A simulated annealing methodology to distribution network design and management”, European Journal of Operational Research, No.144, pp.629–645, 2003.
7. Mester.D, “An Evolutionary Strategies Algorithm for Large Scale Vehicle Routing Problem with Capacitate and Time Windows Restrictions”, Working Paper, Institute of Evolution, University of Haifa, Israel.2002.
8. Park.Y, “A hybrid genetic algorithm for the vehicle scheduling problem with due times and time deadlines”, International Journal of Production Economics, No.73, pp. 175–188, 2001.