Artificial Intelligence Computational Techniques to Optimize a Multi Objective Oriented Distribution Operations

U.S.S. Dharmapriya and S.B. Siyambalapitiya
Department of Engineering Mathematics
Faculty of Engineering, University of Peradeniya, Sri Lanka

A.K. Kulatunga
Department of Production Engineering
Faculty of Engineering, University of Peradeniya, Sri Lanka

Abstract

Artificial Intelligent (AI) techniques make a great influence on real-world distribution operations due to the complexity and the difficulty of finding an optimal solution within the limited time frame. To bridge the gap between standard problems in distribution and the real world problems, in this research, the standard VRP problem is extended to Multi Depot Vehicle Routing Problem with Time Windows and Split Delivery (MDVRPTWSD). The objective of the study is to (a) minimize the overall transportation cost (b) minimize distance (c) fully utilizing the fleets vehicles (d) distribute balanced load throughout the vehicles. The study tries to investigate the applicability of AI techniques to solve the multi objective problem.

Keywords
Artificial Intelligence, Multi Objective, Simulated Annealing, Tabu Search, Vehicle routing problem

1. Introduction
With the technological development, the distribution operations become more complex while creating burning issues in the area of Supply Chain Management. Moreover, it can be seen comparatively high cost allocation from the overall production. Routing problems form a highly-studied family of problems that includes standard problems such as TSP, VRP etc. Although such problems are frequently used to model real cases, they are often set up with the single objective and very few characteristics of real distribution system. However, the majority of the problems encountered in industry, is multi objective oriented and far way from the standard problems in nature. Therefore, this study tries to model the distribution problem as MDVRPTWSD with the thought of addressing the real world distribution. In order to deal with growing distribution network, the single depot which addresses in the VRP is not capable enough to meet with objectives. Therefore, this work considered a distribution network consists of multiple depot, a fleet of homogeneous vehicles stationed at different depots is necessarily satisfying the demand of the customers in their time frame (i.e the time by which a customer's demand has to be satisfied.) Sometimes it is not realistic that a customer's demand must be delivered by a single vehicle. By allowing deliveries to be split, customer can be served by more than one vehicle. Moreover, in real-life, there may be several cost associated with a single tour. Jozefowiez et al. (2008) gives excellent overview on multi objective vehicle routing problems. This study tries to minimize overall transportation cost simultaneously with distance, vehicle space and distributing balanced load through vehicles.

However, with the variation of problem size (complexity), the computational time to finds the optimal results increase exponentially, hence these problems are categorized as NP-hard problems in mathematical terms.It has been proven by many researches, adapting AI techniques consists of many heuristics, near optimal results can be found within reasonably less computational time for NP-hard type problems. For instance, Telfar (1994) presented an overview on applicable heuristic for global optimization while investigating the algorithm performance on TSP. Pisinger and Ropke (2005) presented an unified heuristic which is able to solve five different variant of VRP . They concluded that the proposed heuristic is promising by considering it on standard bench mark problem. Jeon et al (2007) solved VRP using hybrid genetic algorithm. This study suggested a mathematical programming model with new numerical formulas. The process of hybrid genetic algorithm additionally considers the initial population by using both random generation and heuristic techniques. Bell and McMullen (2004) used Ant colony optimization techniques for VRP. Further it is compared with the other artificial intelligent techniques such as TS, SA, GA. It is conclude that the algorithm is successful in finding solutions within 1% of known optimal solutions. Nagy and Salhi (2005) presented a new heuristic for VRP with pickup and delivery system. Rest of the paper is arranged, Section 2 - formulation of distribution problem and mathematical model, Section 3 present methodology it is followed by simulation and results (Section 4) and Conclusion (Section 5).

2. Formulation of Distribution Problem and Mathematical Model

The distribution network considered in this study consists of multiple warehouses, sets of dealers with defined time frame and fleet of homogeneous vehicle. Warehouses are pre located in places where easy to access by vehicle and customers are going to be catered by the most feasible warehouse. The objective of this study is to minimize the overall transportation cost while maintaining the proper load balance among whole distributing vehicles. This problem is formulated as follows. A distribution network consists of sets of customers C = {1,2,……….n} residing at "n" different locations, catered by distributed ware houses (WH_j) where j = 1…….m and m<n. A customer is defined with a demand (q_i) where $q_i>0$ with the time window i.e an interval $[a_i,b_i] \in R$ where a_i and b_i are the earliest and latest time to start to service the customer . Every pair of customers (i,j) where i,j Є C and $i \neq j$ is associated with a traveling distance d_{ij} and traveling time t_{ij}. A fleet of homogeneous vehicle with the capacity of V_c scattered throughout the network, allowing to start from any depot and reach the place where it is requested. In this study, the demand of a customer may be fulfilled by more than one vehicle when the demand of the customer exceeds the vehicle capacity which known as split delivery. The parameters of the distribution network are presented in the Figure1 below. For i^{th} customer considered, defined with delivery amount (q_i), time window $[a_i,b_i]$. Distance and time in between i and j represent in d_{ij} and t_{ij} respectively.

The MDVRPTWSD can be stated as;
For each arc (i,j) where i,j Є C , $i \neq j$ and for each vehicle k, we define X_{ijk} and Y_{ik}.

$$X_{ijk} = \begin{cases} 1 \text{ ; If the vehicle k travel to demand point j directly from demand point i} \\ 0 \text{ ; Otherwise} \end{cases}$$

$$Y_{ik} = \begin{cases} 1 \text{ ; If the demand point i is visited by vehicle k} \\ 0 \text{ ; Otherwise} \end{cases}$$

P_{ik} - Delivery amount at demand point i by vehicle k
Q_i - Demand at customer i
a_i - Earliest arrival time of customer i
b_i - Latest arrival time of customer i
d_{ij} – Distance in between customer i and j

$$Minimize\ Z(W) = \sum_{i=1}^{N} w_n \quad (1)$$

$$w_1 + w_2 = 1 \quad (2)$$

$$w_n = w_1 \times d_{ij} + w_2 \times \left(\frac{1}{Q_i}\right) \quad (3)$$

$$\sum_{k=1}^{u} p_{ik} = q_i \quad (4)$$

$$p_{ik} \leq q_i y_{ik} \tag{5}$$

$$a_j^k \leq a_j^k + t_{ij} \leq l_j^k \tag{6}$$

$$a_j^k \leq l_j^k + t_{ij} \leq l_j^k \tag{7}$$

$$\sum_{i,j=0}^{n} x_{ijk} q_i \leq v_c \tag{8}$$

Equation (1) provides the weighted function of distance traveled and delivery amount. $w_1$and w_2 weightages given to distance and demand respectively.Therefore (1) is selected as the objective function in the view of minimizing the total distance travelled and maximize the delivery. This mathematical model has several limitations and they are given as the constraints in the model. Constraint (4) ensures that a vehicle only serves the demand point visited by the vehicle. Constraint (5) guarantees that the demand of each demand point is totally satisfied. Constraint (6) and (7) refers the time window of a customer and (8) ensures that customer demand does not exceed the vehicle capacity.

3. Methodology

The proposed methodology is arranged in a two stages; initialization and optimization stage. The initial solution is computed by a greedy approach, considering the distance, the vehicle capacity and time window of the demand. Since the multiple warehouses are available, there is a chance of selecting most feasible warehouse considering availability and distance. In the optimization stage, the initial solution is improved with multi objective consideration using TS and SA heuristics.

The flow chart of the proposed method is illustrated in the figure 1.At the very beginning of the process, it is required to get all the information about customers (i.e location, distance in between each customers and warehouses, demand, etc). Based on the above, the shortest distance of each demand point is generated by using Dijsktra algorithm. All received tasks have to be processed in such a way that tasks are separated according to the date. Thereafter, they are sorted out by earliest arrival time in order to give the most priority to urgent task. The selection of warehouse (depot) is done considering the closeness to the first task of the prepared task list and the availability of the goods in the warehouse. If the vehicle is capable of loading more tasks, they are selected based on distance. Moreover, the selected first closest task should satisfy the time window or else algorithms consider the next closest task. This will repeat until the vehicle is fully loaded with the tasks and start with the next vehicle until the all tasks are assigned.

At the optimization stage, the initial solution is improved by TS and SA. TS is a meta-heuristic that guides a local search procedure to explore the solution space beyond the local optimality. There are number of local search methodologies which can be used with TS. One of the main components of TS is its adaptive memory. Thereby, many combinations can be checked in the second stage and capability of storing many solutions is possible with tabu search. Selection of best solution and replacing the worst by better solution are also advantages of TS.

The two local search techniques used in TS is Relocate operator and Exchange Operator. Above two move operators are evaluated on same pair of routes and the best operator isselected based the traveling cost. Assume we have two routes R_k and R_h where i Є R_k and j Є R_h .

1. Relocate operator :- Remove i from R_k and insert it into R_h.
2. Exchange Operator: - Exchange customer i from R_k and customer j from R_h .

Each operation is done on the two customers considered from two routes (i.e customer i from R_k and j from R_h). Once performing the operation, newly entered customer should satisfy the time window of the route which it is entered and the capacity of the vehicle. If it satisfies the conditions, the total travelled distance is calculated. If the distance corresponding to newly generated route is greater than the previous one, then that pair of routes is entered into the tabu list. The procedure is continued with the other tasks and stored in the tabu list. When the tabu memory exceeds it's defined capacity and still we are remaining with more combinations to check, worst task in the tabu list is replaced by new better task. Likewise, both operators are performed on each pair of routes and select the most profitable route.

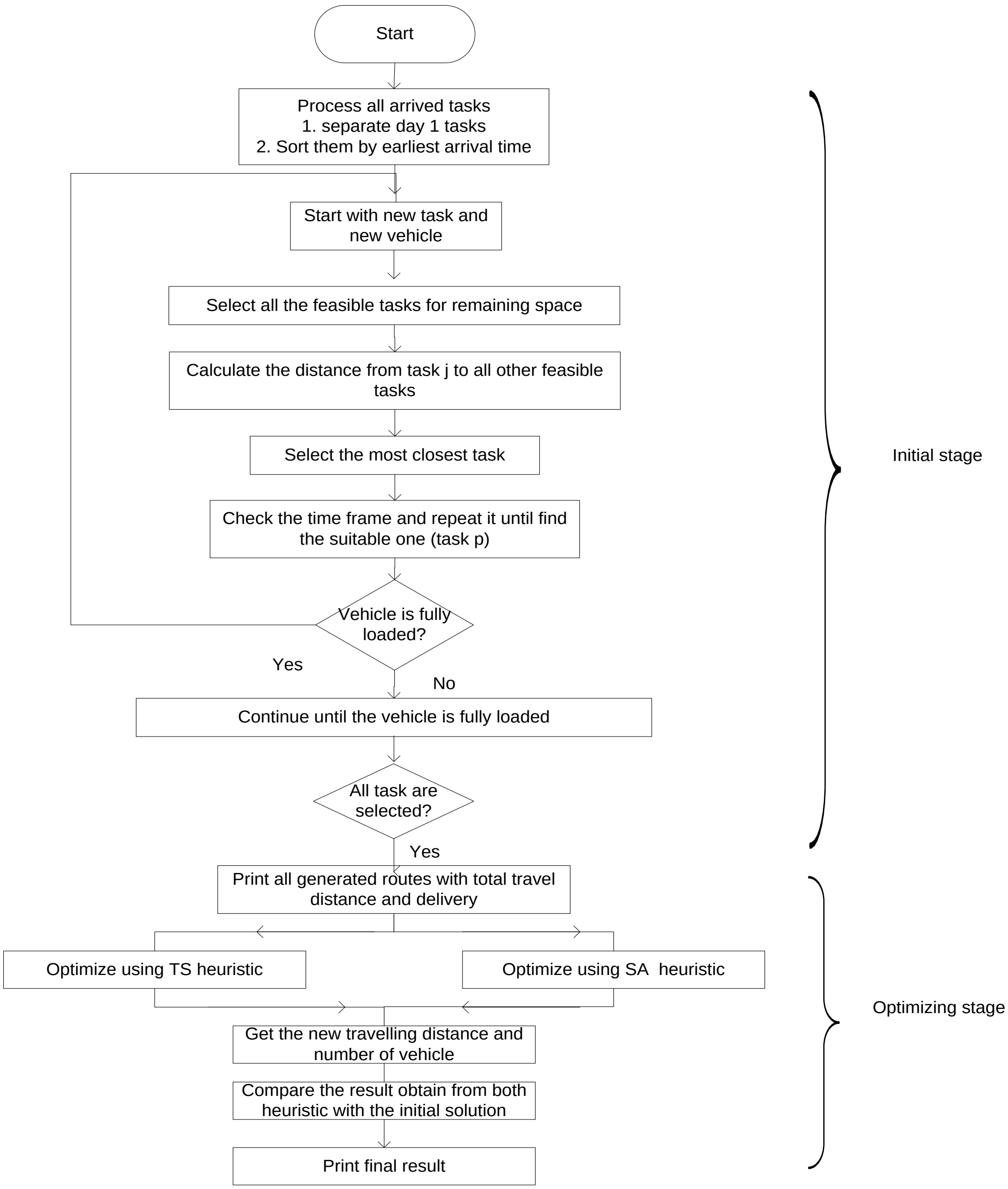

Figure 1: Flow chart of the proposed methodology

4. Simulation and Results

The considered distribution network consists of 50 customers, 6 warehouses and 15 vehicles with the capacity of 40 units. Parameter of the SA are starting temperature 100, cooling rate 0.95. Randomly generated data sets with different sizes are used in the case studies. This study tries to convince the significance of doing split delivery, effectiveness of different AI techniques (SA,TS) on initial solution in single objective and multi objective environment. As reported in Table 1, the splitting option is favorable in terms of number of vehicles used and the number of completed tasks. This comparison was done using the greedy approach at the initial stage. Table 2 shows the improvement of the initial solution with SA and TS heuristics in single objective environment (i.e minimize the travelling distance) and in multi objective environment (minimize the travelling distance, giving higher priority to high demanded tasks while making equal work load throughout every vehicles). Results reveals that better results can be obtained in multi objective oriented problem for same initial solution,. However, results shows that the TS out perform the solution quality in single objective and multi objective environment.

Table 2: Heuristic performance in single objective and multi objective environment

Case No.		No. of vehicles	Traveled distance	Delivery amount
1	Initial solution	6	186	130
	Operator 1	6/6	120/100	130
	Operator 2	5/4	135/95	130
	SA	6/6	145/135	130
2	Initial solution	3	92	95
	Operator 1	3/3	86/84	95
	Operator 2	3/2	82/75	95
	SA	3/3	90/90	95

5. Conclusions

AI techniques such as SA and TS have been used to solve complex multi objective MDVRPSDTW problem. Numbers of experiments have been carried out to convince the significance of excluding and including the split option. It reveals that including split delivery is beneficial in terms of number of vehicles, number of completed tasks when limited number of vehicles available. We have investigated how the heuristic techniques perform on initial solution in single objective (minimize the travelling distance). Both heuristics are able to find reasonably good results within shorter time period. However, TS based results outperform the solution in quality. Moreover, the experiments done in the multi objective environment demonstrate that high demanded task has a chance of early supplement while travelling through shorter route. It can be concluded that AI techniques can be used to find near optimal results with considerable time interval for complex MDVRPSDTW. In future, this research will be extended to develop a hybrid algorithm to improve the solution quality further.

References

1. Telfar, G.,2004, "Generally Applicable Heuristics for global optimization: An investigation of Algorithms Performance for the Euclidean Traveling Salesman Problem"
2. William, H., George T.S. H., Ping, J., Henry, C.W.L.(2008) "A hybrid genetic algorithm for the multi-depot vehicle routing problem", Engineering Applications of Artificial Intelligence, Vol.21 ,pp. 548–557.
3. Suk-Tae,B.,Heung,S., Hwang,Gyu-Sung,C.,Meng-Jong,G.2007, "Integrated GA-VRP solver for multi-depot system",Computers & Industrial Engineering,Vol. 53,pp. 233–240
4. Mingzhou,J., Kai,L., Royce, O.B.2007, "A two-stage algorithm with valid inequalities for the split delivery vehicle routing problem", Int. J. Production Economics, Vol.105,pp. 228–242
5. Patrıcia,B., Hugo,T.Y.Y.,2008, "Scatter search for a real-life heterogeneous fleet vehicle routing problem with time windows and split deliveries in Brazil," European Journal of Operational Research.
6. Bent.R, Hentenryck.P.V., 2004, " A two-stage hybrid local search for the vehicle routing problem with time windows" , Transportation science.
7. Jeon, G., Leep, H.R. and Shim, J.Y.,2007 'A vehicle routing problem solved by using a hybrid genetic algorithm',Computers & Industrial Engineering,pp.680-692.
8. Bella, J.E. and McMullenb, P.R.,2004,' Ant colony optimization techniques for the vehicle routing problem', Advanced Engineering Informatics,pp.41-48.
9. Jozefowiez, N.,Semet, F.,Talbi, E.,2008, " Multi-objective vehicle routing problems", European journal of Operations Research 189.