An Application of Analytic Hierarchy Process in Vehicle Routing Problem

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Abstract

Vehicle Routing Problem (VRP) facilitates on finding a set of trips, one for each vehicle and to deliver known quantities of goods from a single depot to a set of geographically dispersed customers. This paper proposes an effective hybrid approach that combines customer prioritization with the Clarke and Wright's savings algorithm to solve the capacitated vehicle routing problem. In this model, in addition to traditional objective of resolving vehicle routing problem, the customer satisfaction have been taken into account. Initially, all the customers have been clustered with the help of Clarke and Wright's saving algorithm and later the customers have been prioritized on assigning optimal route using Analytic Hierarchy Process (AHP) as a Multi Criteria Decision Making (MCDM) tool. The highlight of this research is to diminish the total transportation cost without violating the vehicle capacity and ultimately improve the customer satisfaction.

Keywords

Vehicle Routing Problem, Clarke and Wright's saving algorithm, customer prioritization, Analytic Hierarchy Process, Multi Criteria Decision Making

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1 Introduction

Transportation has evolved as an important domain of human activity over ages. It supports and strengthens other social and economic activities including manufacturing. The Vehicle Routing Problem (VRP) is an important operational decision in the distribution network and has a significant role in cost reduction and service improvement which facilitates the routing and scheduling of deliveries. In VRP, a fixed fleet of delivery vehicles of uniform capacity is used to provide known customer demands for a single commodity from a common depot by travelling minimum distance with minimum transit cost. The VRP is a combinatorial optimization and integer programming problem seeking to serve a number of customers with a fleet of vehicles. Managers, on the other hand encounter problems in assessing optimal route and providing customer delivery at right locations and at right time to achieve desired level of customer satisfaction.

The success of VRP operation turns on its ability to decrease transportation and delivery cost while providing the promised level of responsiveness to the customer. Given a set of customer orders, the goal is to design route and schedule delivery vehicles such that costs incurred to meet delivery promises are as low as possible.

A classical route construction heuristic was the sequential insertion algorithm by Mole and Jameson (1976). The algorithm uses selection and insertion criterion were the evaluation of the extra distance resulting from the insertion of an unrouted customer k between two consecutive customers i and j of the current route had been attempted. After each insertion trial, the current route was possibly improved by using 3-opt procedure.

A general and effective two-step insertion heuristic was proposed by Christofides et al. (1979). In first step, a sequential insertion algorithm was used to determine a set of feasible routes while the second step was a parallel insertion approach. For each route determined in first step, an envoy customer was selected and a set of single-customer routes was initialized with these customers. The remaining unrouted customers were then inserted by using a regret criterion, where the difference between the best and the second-best insertion cost were

accounted, and partial routes were improved by means of 3-opt procedure. The resulting algorithm was superior to that of Mole and Jameson and symbolized a good compromise between effectiveness and efficiency.

The sweep algorithm, introduced by Wren (1971), Wren and Holliday (1972), and Gillett and Miller (1974), has often been referred to as the first example of cluster first- route second approach applied to planar VRP instances. The algorithm starts with an arbitrary customer and then sequentially assigns the remaining customers to the current vehicle by considering them in the order of increasing polar angle with respect to the depot and the initial customer. When the current customer cannot be feasibly assigned to the current vehicle, a new route was initialized accordingly. Once all customers were assigned to vehicles, each route was separately defined by solving a Travelling Salesman Problem (TSP).

The Fisher and Jaikumar (1981) algorithm unravels the clustering step by means of Generalized Assignment Problem (GAP) which calls for determination of a minimum cost assignment of items to a given set of bins of capacity Q, in which the items were characterized by a weight and an assignment cost for each bin. Each vehicle was assigned an envoy customer, called a seed, and assignment cost of a customer to a vehicle was considered equal to its distance to the seed. GAP was then solved, either optimally or heuristically, and final routes were determined by solving a TSP on each cluster.

Another two-phase method working with a fixed number of vehicles m was described by Bramel and Simchi-Levi (1995). This algorithm determined route seeds by solving a capacitated location problem, where "m" customers are selected by minimizing the total distance between each customer and its closest seed, and by imposing that the total demand associated with each seed be at most Q. Once seeds have been determined and the single-customer routes were initialized, the remaining customers were inserted in the current routes by minimizing insertion costs. Diverse techniques of approximating the insertion cost were proposed and analysed. It is worth noting that cluster-first-route second approaches just allow for a direct control of the number of routes in the final solution, whereas the sweep algorithm does not. The performance of these algorithms is generally comparable to that of route construction algorithms in terms of effectiveness.

A different family of two-phase methods is the class of so-called petal algorithms. These generate a large set of feasible routes, called petals, and select the final subset by solving a set partitioning model. Foster and Ryan (1976) and Ryan et al. (1993) have proposed heuristic rules for determining the set of routes to be selected, while Renaud et al. (1996) have described an extension that considers more involved configurations, called 2-petals, consisting of two embedded or intersecting routes. The overall performance of these algorithms is generally superior to that of the sweep algorithm.

Belatedly researchers realized that real time event information and multimodal planning can be massively required to operate within a short time period and at a wide spatial scale. Journey Planners have thought of a sustainable business model as the one by Vassilis Spitadakis and Maria Fostieri (2012). Their WISETRIP innovative journey planner provides multimodal trip information sourced from variant journey planners utilizing a challenging but simple communication interface to smoothen connection of heterogeneous planners without sacrificing functional sufficiency. Additionally, unique personalized services delivery was achieved wherein users could select their trips, build personal schedule of notifications, configure alerts that assist trip execution and enable continuous validation of trip data. Their study surfaces facts that daily predicaments in transportation like minor disrupts or even personal problems and preferences of individuals could surpass a wide and complex grid of changeable parameters for trip performance. Their journey planning engine highlights the neediness to accommodate variety of user groups, namely the elderly and disabled, the eco-sensitive users, the green route proposers, and travellers who often enroute urgent disruptions.

Recent academic literature regarding daily activity chain optimization stresses on topics like activity-based trip chaining, mode choice, travel demand management and flexible mobility options. Domokos Esztergár Kiss et al. (2016) in their recent paper deal with the optimization of daily activity chains as a series of activities during a certain time period for several parameters were user preferences for choosing the best set of activities lie upon practical quantifiable factors. Classification parameters connected to the user component type namely, age, gender, occupation, income, car ownership, family status had been deployed to categorize users into user groups as against weights of locations. The outcomes could be appreciated much as connectivity to the user, the chosen transportation mode and the location type of the activity was all mapped and a generalized weighting model for the optimization was created.

Development of adaptive traveller information systems based on Artificial Intelligence is still in its formative years. A fair attempt was made in this direction by Theo A. Arentze (2013) were a Multi modal routing model using Bayesian learning of preferences, defining the functional relationship between preference parameters and choice behaviour were focussed. Preferences represented parameters of network link cost functions in the routing system and the author had proposed a method to incorporate the learning of users preferences in a route recommendation system. Unlike conventional Bayesian methods, this paper intends reduction of computation time by assuming sequential processing of parameters and systematic sampling of the parameter space.

Conclusively, in route-first-cluster-second methods, a giant TSP tour over all customers is constructed in a first phase and later subdivided into feasible routes. Research trials of such

algorithms were proposed by Beasley (1983), Haimovich and RinnooyKan (1985), and Bertsimas and Simchi-Levi (1996).

2 Problem Formulation

The first and foremost famous heuristic of allied research was proposed by Clarke and Wright (1964), based on the concept of saving, which was an estimate of the cost reduction obtained by serving two customers sequentially on the same route, rather than in two separate ones. If i is the last customer of a route and j is the first customer of another route, the associated saving is defined as sij =ci0 +c0j −cij. If sij is positive, then serving i and j consecutively in a route is profitable. The Clarke and Wright algorithm considered all customer pairs and sorted the savings in non-increasing order. Starting with a solution in which each customer appears separately in a route, the customer pair list was examined and two routes were merged whenever feasible. Generally, a route merge was accepted only if the associated saving was nonnegative but, if the number of vehicles is to be minimized, then negative saving merges were also considered.

A mathematical explanation of VRP as defined by Boonkleaw et al. (2009) can be applied for case under limelight. Let G = (V, A) be a network where V = {0, 1, …, n} is the vertex set and A ⊆ V×V is the arc set. Vertex 0 is the depot and V\{0} is the set of locations on the road network. Associated with vertex i∈ V\{0} is a non-negative demand di. The parameter cij represents a non-negative cost (traveling cost in this case) between vertices i and j. The parameters K and Uk are the number of vehicles and the capacity of vehicle k, respectively. A three-index integer programming formulation is presented here where binary variables xijk denotes the number of times arc (i,j) ∈ A is traversed by vehicle k (k = 1,…,K) in the optimal solution. In addition, there are binary variables yik (i∈ V; k = 1,…,K) that take a value of 1 if vertex i is visited by vehicle k in the optimal solution and take a value of 0, otherwise. The mathematical formulation of the problem is as follows

$$\min \sum_{(i,j)\in A} c_{ij} \sum_{k=1}^{K} x_{ijk}. \tag{1}$$

Subject to

$$\sum_{k=1}^{K} y_{ik} = 1 \quad \forall i \in V \setminus \{0\} \tag{2}$$

$$\sum_{k=1}^{K} y_{0k} = K \tag{3}$$

$$\sum_{j\in V\setminus\{i\}} x_{ijk} = y_{ik} \quad \forall i \in V, k = 1,\ldots,K \tag{4}$$

$$\sum_{j\in V\setminus\{i\}} x_{jik} = y_{ik} \quad \forall i \in V, k = 1,\ldots,K \tag{5}$$

$$\sum_{i\in V\setminus\{0\}} d_i.y_{ik} < U_k \quad \forall k = 1,\ldots,K \tag{6}$$

$$\sum_{i\in S}\sum_{j\in S\setminus\{i\}} x_{ijk} \le |S|-1 \quad \forall S \subseteq V\{0\}, |S| \ge 2, \quad k = 1,\ldots,K \tag{7}$$

$$y_{ik} \in \{0,1\} \quad \forall i \in V, k = 1,\ldots,K \tag{8}$$

$$x_{ijk} \in \{0,1\} \quad \forall (i,j) \in A, k = 1,\ldots,K. \tag{9}$$

Eq. (1) represents the objective function of this problem which is to minimize total travel time of the operations. Constraints (2), (3), (4) and (5) ensure that each customer is visited exactly once, that k vehicles leave the depot, and that the same vehicle enters and leaves a given customer vertex, respectively. Constraints (6) denotes the capacity restrictions for each vehicle k. Constraint (7) are sub-tour elimination constraints for each vehicle, where S is a subset of the stops that does not include the depot.

2.1 Problem Assumption and Constraints

Assumptions during problem formulation include:
1. Each route will start from Depot and end at the Depot.
2. Cost of a route is proportional to the distance travelled.
3. Travel distance between each customer is known and accurate.
4. Demands of each of the customers are known and certain.
5. Demand at each stop cannot segmented.

Constraints of the problem include:
1. Maximum availability of 5 vehicles.
2. Maximum load for each vehicle is 80 packages.

3 About the Industry and its VRP

Athammal spinners was established in 1993 with a capacity of 12,000 spindles. The firm in located at Periyanaickenpalayam, Coimbatore, Tamil Nadu, India and produces 2 tons of cotton hanks per day. In the textile industry, a hank is a unit of yarn or twine in a coiled form. The potential list of customers of hanks in and around Coimbatore, concentrated near Tiruppur, Erode, Karur and Namakkal and their demand is exhibited. (Table 1)

The finished product is stored and delivered by means of packages (1 package = 94 kg of bundled cotton hanks). The firm owns 5 vehicles of maximum capacity of 80 packages which is used for distribution of their product from the firm to all their customers on weekly basis. The existing distribution route (Table 2) is based on driver's previous trials and experience. The company does not follow any scientific and organized method to deliver its products. Thus, the company faces high transportation cost and customer dissatisfaction which provokes the need for a structured methodology in its VRP.

Table 1 List of customers

no	Customer list	Location	Demand (in packages)
Depot	**Athammal Spinners**	**Periyanaickenpalayam**	-
C1	Agarram textile mills	Dharapuram	8
C2	AKR tex	Tirupur	24
C3	Andavar textile mills	Karumathampatti	15
C4	Balamurugan Textiles	Erode	12
C5	Enjoy textile	Tirupur	22
C6	Global Textiles	Karur	25
C7	Guruvayurappan Tex	Udumalpet	10
C8	Kesharinandan knit Fabrics	Avinashi	13
C9	Motherland Textile	Karumathampatti	22
C10	PSM Textiles	Karur	35
C11	RevathiTex	Vellakovil	10
C12	Santha Weaving Mills	Kangayam	15
C13	SCM Garments	Avinashi	24
C14	SreeVari Textiles	Erode	40
C15	Sri Amman Textiles	Tiruchengode	8
C16	Thaiyalnayagi Textiles	Bhavani	20
C17	Velavan Textiles	Perundurai	9
C18	Vimal Warping	Bhavani	30
C19	Vigneshwara Textiles	Bhavani	15
C20	YazhiniTex	Vijayamangalam	20

Table 2 Existing route

Vehicle no	ROUTE	Distance (kms)	Load(packages)
V1	Depot-C10-C7-C1-C9-depot	401	75
V2	Depot-C13-C15-C11-C12-C3-depot	318	72
V3	Depot-C19-C14-C6-depot	348	80
V4	Depot-C8-C4-C16-C18-depot	262	75
V5	Depot-C5-C2-C20-C17-depot	189	74
	TOTAL	1518	

4 Customers Clustering

The Clarke and Wright algorithm is the most popular heuristic algorithm for clustering of customers in VRP. The algorithm calculates all the savings S_{ij} between customers i and j.

Assuming that d_{i0} is the cost of travelling from the depot to customer i and d_{ij} is the cost of travelling from customer i to j. The following is a description of the Clarke and Wright algorithm to solve the VRP:

Step 1: Compute the distance matrix with the help of google maps. (Fig. 1)

Step 2: Compute the savings $S_{ij} = d_{i0}+d_{0j} − d_{ij}$ for i, j = 1,…, 20 and i≠j. (Fig. 2)

Step 3: Rank the savings S_{ij} and list them in descending order. Create the savings list. Process the savings list beginning with the highest entry in the list (the largest S_{ij}). For the savings under consideration (S_{ij}), include link (i, j) in a route if no route constraints will be violated through the inclusion of (i, j). However, the following three cases need to be considered.

Case 1: If neither i nor j have already been assigned to a route, then a new route is initiated including both i and j.

Case 2: If exactly one of the two points (i or j) has already been included in an existing route and that point is not interior to that route (a point is interior to a route if it is not adjacent to the depot in the order of traversal of points), then the link (i, j) is added to that same route. If the point is interior and not violating the capacity then add (i, j) to the same route. If it is violating the capacity make a new route with the point (customer) i.

Case 3: If both i and j have already been included in two different existing routes and neither point is interior to its route, then the two routes are merged by connecting i and j. If they are interior then the merge cannot be done.

Step 4: If the savings list S_{ij} has not been exhausted, return to Step 3 and continue the process until the clustering of customers into each vehicle is finalised (Table 3).

5 Customer Prioritizing using AHP:

Customer prioritization is a Multiple Criteria Decision-Making (MCDM) problem. A review of the literature shows that the AHP method to be one of the most commonly applied methods in practice. AHP is relatively simple to use and understand and

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
0	0																				
1	102	0																			
2	59	53	0																		
3	43	66	20	0																	
4	109	85	62	82	0																
5	54	57	4	23	65	0															
6	152	65	87	109	67	91	0														
7	114	34	76	78	110	80	101	0													
8	45	72	18	17	65	16	112	85	0												
9	39	73	25	8	78	27	116	86	16	0											
10	154	67	89	111	70	93	5	101	112	119	0										
11	112	30	47	69	53	50	43	63	70	77	44	0									
12	82	38	30	45	54	33	65	67	51	53	66	24	0								
13	42	73	19	15	65	16	112	87	3	13	113	71	51	0							
14	106	82	57	78	3	57	65	108	62	78	66	51	52	64	0						
15	140	102	94	114	22	82	61	127	98	112	59	63	71	101	24	0					
16	109	93	63	82	14	61	86	118	67	81	84	66	62	70	14	34	0				
17	89	76	37	63	27	35	77	101	47	61	77	58	46	43	24	59	28	0			
18	113	97	67	86	14	64	82	121	72	84	80	71	65	73	17	26	5	31	0		
19	113	96	67	87	13	65	80	122	71	85	78	72	66	74	18	24	7	32	4	0	
20	77	73	31	51	35	29	84	100	36	49	85	56	40	38	32	68	37	11	40	42	0

Fig. 1 Distance matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0																			
2	108	0																		
3	79	82	0																	
4	126	106	70	0																
5	99	109	74	98	0															
6	189	124	86	194	115	0														
7	182	97	79	113	88	165	0													
8	75	86	71	89	83	85	74	0												
9	68	73	74	70	66	75	67	68	0											
10	189	124	86	193	115	301	167	87	74	0										
11	184	124	86	168	116	221	163	87	74	222	0									
12	146	111	80	137	103	169	129	76	68	170	170	0								
13	71	82	70	86	80	82	69	84	68	83	83	73	0							
14	126	108	71	212	103	193	112	89	67	194	167	136	84	0						
15	140	105	69	227	112	230	127	87	67	235	189	151	81	222	0					
16	118	105	70	204	102	175	105	87	67	179	155	129	81	201	215	0				
17	115	111	69	171	108	164	102	87	67	166	143	125	88	171	170	170	0			
18	118	105	70	208	103	183	106	86	68	187	154	130	82	202	227	217	171	0		
19	119	105	69	209	102	185	105	87	67	189	153	129	81	201	229	215	170	222	0	
20	106	105	69	151	102	145	91	86	67	146	133	119	81	151	149	149	155	150	148	0

Fig. 2 Saving matrix

proves an ideal method for ranking alternatives when multiple criteria and sub criteria are present in the decision-making process.

AHP is often considered as a supplier selection method because it allows decision makers to rank suppliers based on the relative importance of the criteria and suitability of the suppliers. AHP offers a methodology to rank alternative courses of action based on the decision maker's judgments concerning the importance of the criteria and the extent to which they are met by each alternative.

5.1 Steps in AHP

Step1. List Decision Criteria (DC) for customer prioritization.
Step2. Pair wise comparison of each criteria to obtain the weight of each criteria.

Step3. Pair wise comparison of customers with respect to each criteria to obtain the weight.
Step4. Calculation of overall weight.
Step5. Prioritize the customer based on weight.

Table 3 Clustered list of customers

VEHICLE NO	LIST OF CUSTOMERS	TOTAL LOAD (packages)
V1	C6, C10, C11, C15	78
V2	C4, C16, C18, C19	77
V3	C1, C7, C14, C17	67
V4	C2, C5, C12, C20	79
V5	C3, C8, C9, C13	74

Step 1: List DC for customer prioritization:

i. Customer credit of future business opportunity. (DC1)
ii. The potential profit rate per unit of time. (DC2)
iii. The negotiability level of payment for the order. (DC3)
iv. The level of trust between customer and company. (DC4)

Step 2: Pair wise comparison of each criteria to obtain the weight of each criteria

The rating for each comparison was made a consultation with academic and industrial experts based on AHP rating scales (Table 4). The pairwise comparison between each criteria, thus obtained is portrayed (Table 5).

Table 4 AHP Rating Scales

Rating scale	
Verbal judgment of preference	**Numerical rating**
Extremely preferred	9
Very strongly preferred	7
Strong preferred	5
Moderately preferred	3
Equally preferred	1

Table 5 Rating of Each Criteria

	DC1	DC2	DC3	DC4	Weight
DC1	1	1/5	1	1/3	0.097
DC2	5	1	5	3	0.555
DC3	1	1/5	1	1/3	0.097
DC4	3	1/3	3	1	0.251

Step 3: Pair wise comparison of customers with respect to each criteria to obtain the weight:

i. Customer credit of future business opportunity. (DC1)

Customer credit of future business opportunity has an important effect on the decision of accepting or rejecting an order. Rejecting an order may oblige the customer to contract with other suppliers and may result in getting no future orders from the customer. Hence, firms may sometimes accept an order with lower potential profit rate per unit of time comparing to the other possible orders to ascertain future business opportunities. The pair wise comparison of customers with respect to customer credit of future business opportunity is exhibited (Fig. 3).

ii. The potential profit rate per unit of time. (DC2)

Profit maximization is a vital requirement and primary objective for all profit-making organizations to survive. But, an order with higher profit margin but a longer operation time may not be profitable compared to an order with lower profit margin but a shorter operation time. Thus, potential profit rate, which represents profit per unit of time is selected as a factor for the customer order selection problem. The pair wise comparison of customers with respect to potential profit rate per unit of time is exhibited (Fig. 4).

iii. The negotiability level of payment for the order. (DC3)

The tardiness and bargaining of price can be regarded as major functions of total profit. They are the important indicators of a successful cooperation between the firm and the customer as the primary objective is to maximize profit. The pair wise comparison of customers with respect to negotiability level of payment for the order is exhibited (Fig. 5).

iv. The level of trust between customer and company. (DC4)

Trust is defined as the willingness to be vulnerable. In business, trust involves honesty and dependability between partners. The level of trust between customer and company depends upon customer's financial status, past history of payment and backlog. The pair wise comparison of customers with respect to level of trust between customer and company is exhibited (Fig. 6).

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	W
C1	1	1/3	1	1/3	1/7	1/5	1	1/3	1/3	1/5	3	1/3	3	1	1/3	1/3	3	1/7	1	1/5	0.0185
C2	3	1	3	1	1/5	1/3	3	1	1	1/3	5	1	5	3	1	1	5	1/3	3	1/3	0.0432
C3	1	1/3	1	1/3	1/7	1/5	1	1/3	1/3	1/5	3	1/3	3	1	1/3	1/3	3	1/7	1	1/5	0.0185
C4	3	1	3	1	1/5	1/3	3	1	1	1/3	5	1	5	3	1	1	5	1/3	3	1/3	0.0432
C5	7	5	7	5	1	3	7	5	5	3	9	5	9	7	5	5	9	1	7	3	0.1648
C6	5	3	5	3	1/3	1	5	3	3	1	7	3	7	5	3	3	7	1/3	5	1	0.0911
C7	1	1/3	1	1/3	1/7	1/5	1	1/3	1/3	1/5	3	1/3	3	1	1/3	1/3	3	1/3	1	1/5	0.0185
C8	3	1	3	1	1/5	1/3	3	1	1	1/3	5	1	5	3	1	1	5	1/3	3	1/3	0.0432
C9	3	1	3	1	1/5	1/3	3	1	1	1/3	5	1	5	3	1	1	5	1/3	3	1/3	0.0432
C10	5	3	5	3	1/3	1	5	3	3	1	7	3	7	5	3	3	7	1/3	5	1	0.0911
C11	1/3	1/5	1/3	1/5	1/9	1/7	1/3	1/5	1/5	1/7	1	1/5	1	1/3	1/5	1/5	1	1/9	1/3	1/7	0.0093
C12	3	1	3	1	1/5	1/3	3	1	1	1/3	5	1	5	3	1	1	5	1/3	3	1/3	0.0432
C13	1/3	1/5	1/3	1/5	1/9	1/7	1/3	1/5	1/5	1/7	1	1/5	1	1/3	1/5	1/5	1	1/9	1/3	1/7	0.0093
C14	1	1/3	1	1/3	1/7	1/5	1	1/3	1/3	1/5	3	1/3	3	1	1/3	1/3	3	1/7	1	1/5	0.0185
C15	3	1	3	1	1/5	1/3	3	1	1	1/3	5	1	5	3	1	1	5	1/3	3	1/3	0.0432
C16	3	1	3	1	1/5	1/3	3	1	1	1/3	5	1	5	3	1	1	5	1/3	3	1/3	0.0432
C17	1/3	1/5	1/3	1/5	1/9	1/7	1/3	1/5	1/5	1/7	1	1/5	1	1/3	1/5	1/5	1	1/9	1/3	1/7	0.0093
C18	7	3	7	3	1	3	7	3	3	3	9	3	9	7	3	3	9	1	7	3	0.1381
C19	1	1/3	1	1/3	1/7	1/5	1	1/3	1/3	1/5	3	1/3	3	1	1/3	1/3	3	1/7	1	1/5	0.0185
C20	5	3	5	3	1/3	1	5	3	3	1	7	3	7	5	3	3	7	1/3	5	1	0.0911

Fig. 3 Rating of customers with respect to customer credit of future business opportunity

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	W
C1	1	1	1/5	5	3	1	5	3	1	3	1/5	5	5	1/5	3	1/5	1/3	1	3	1/3	0.0380
C2	1	1	1/5	5	3	1	5	5	1	3	1/5	5	5	1/5	5	1/5	1/3	1	1	1/3	0.0391
C3	5	5	1	9	7	5	9	7	5	7	1	9	7	1	9	1	3	5	7	3	0.1305
C4	1/5	1/5	1/9	1	1/3	1/5	1	1/3	1/5	1/3	1/5	3	1	1/9	1	1/9	1/7	1/5	1/3	1/7	0.0111
C5	1/3	1/3	1/7	3	1	1/3	3	1	1/3	1	1/7	3	3	1/7	3	1/7	1/5	1/3	1	1/5	0.0194
C6	1	1	1/5	5	3	1	5	3	1	3	1/5	5	5	1/5	5	1/5	1/3	1	3	1/3	0.0391
C7	1/5	1/5	1/9	1	1/3	1/5	1	1/3	1/7	1/3	1/9	1	1	1/9	1	1/9	1/7	1/5	1/3	1/7	0.0093
C8	1/3	1/5	1/7	3	1	1/3	3	1	1/3	1	1/7	3	5	1/7	3	1/7	1/5	1/3	1	1/5	0.0203
C9	1	1	1/5	5	3	1	7	3	1	3	1/5	5	5	1/5	5	1/7	1/3	1	3	1/3	0.0398
C10	1/3	1/3	1/7	3	1	1/3	3	1	1/3	1	1/7	1	3	1/7	1	1/7	1/5	1/3	1	1/3	0.0175
C11	5	5	1	5	7	5	9	7	5	7	1	9	9	1	7	1	3	5	7	3	0.1282
C12	1/5	1/5	1/9	1/3	1/3	1/5	1	1/3	1/5	1	1/9	1	1	1/9	1	1/9	1/7	1/5	1/3	1/7	0.0096
C13	1/5	1/5	1/7	1	1/3	1/5	1	1/5	1/5	1/3	1/9	1	1	1/9	1	1/9	1/7	1/5	1/3	1/7	0.0095
C14	5	5	1	9	7	5	9	7	5	7	1	9	9	1	9	1	3	5	7	5	0.1368
C15	1/3	1/5	1/9	1	1/3	1/5	1	1/3	1/5	1	1/7	1	1	1/9	1	1/9	1/7	1/5	1/3	1/7	0.0104
C16	5	5	1	9	7	5	9	7	7	7	1	9	9	1	9	1	3	5	7	3	0.1344
C17	3	3	1/3	7	5	3	7	5	3	5	1/3	7	7	1/3	7	1/3	1	3	5	1	0.0738
C18	1	1	1/5	5	3	1	5	3	1	3	1/5	5	5	1/5	5	1/5	1/3	1	5	1/3	0.0408
C19	1/3	1	1/7	3	1	1/3	3	1	1/3	1	1/7	3	3	1/7	3	1/7	1/5	1/5	1	1/5	0.0202
C20	3	3	1/3	7	5	3	7	5	3	3	1/3	7	7	1/5	7	1/3	1	3	5	1	0.0711

Fig. 4 Rating of customers with respect to the potential profit rate per unit of time

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	W
C1	1	5	9	5	3	9	5	7	1	5	9	3	7	7	3	7	5	1	9	1	0.1258
C2	1/5	1	5	3	1/3	3	1	3	1/5	1	5	1/3	3	7	1/3	3	1	1/3	5	1/3	0.0388
C3	1/9	1/5	1	1/3	1/7	1	1/5	1/3	1/9	1/5	3	1/7	1/3	1	1/5	1/3	1/5	1/9	1	1/9	0.0101
C4	1/5	1/3	3	1	1/5	1	1/3	3	1/7	1/3	3	1/5	1	5	1/5	1	1/3	1/9	3	1/5	0.0207
C5	1/3	3	7	5	1	5	3	5	1/3	3	7	1	5	7	1	5	1	3	7	1	0.0846
C6	1/9	1/3	1	1	1/5	1	1/5	1/3	1/9	1/5	3	1/7	1/3	1	1/7	1/3	1/5	1/9	3	1/7	0.0122
C7	1/5	1	5	3	1/3	5	1	3	1/5	1	5	1/3	1	5	1/3	3	3	1/5	5	1/3	0.0389
C8	1/7	1/3	3	1/3	1/5	3	1/3	1	1/7	1/3	3	1/5	1	3	1/5	1	1/3	1/7	1	1/5	0.0173
C9	1	5	9	7	3	9	5	7	1	5	9	3	5	9	3	7	5	1	7	3	0.1328
C10	1/5	1	5	3	1/3	5	1	3	1/5	1	5	1/3	1	5	1/3	1	3	1/5	5	1/3	0.0372
C11	1/9	1/5	1/3	1/3	1/7	1/3	1/5	1/3	1/9	1/5	1	1/7	1/3	3	1/7	1/3	1/5	1/9	1/3	1/7	0.0090
C12	1/3	3	7	5	1	7	3	5	1/3	3	7	1	5	7	1	5	3	1/5	7	1	0.0725
C13	1/7	1/3	3	1	1/5	3	1	1	1/5	1	3	1/5	1	5	1/5	1	1/3	1/7	1	1/5	0.0214
C14	1/7	1/7	1	1/5	1/7	1	1/5	1/3	1/9	1/5	1/3	1/7	1/5	1	1/7	1/3	1/5	1/7	3	1/7	0.0099
C15	1/3	3	5	5	1	7	3	5	1/3	3	7	1	5	7	1	5	3	1/5	7	1	0.0714
C16	1/7	1/3	3	1	1/5	3	1/3	1	1/7	1	3	1/5	1	3	1/5	1	1/3	1/9	3	1/5	0.0198
C17	1/5	1	5	3	1	5	1/3	3	1/5	1/3	5	1/3	3	5	1/3	3	1	1/5	5	1/5	0.0377
C18	1	3	9	9	3	9	5	7	1	5	9	5	7	7	5	9	5	1	9	3	0.1462
C19	1/9	1/5	1	1/3	1/7	1/3	1/5	1	1/7	1/5	3	1/7	1	1/3	1/7	1/3	1/5	1/9	1	1/7	0.0108
C20	1	3	9	5	1	7	3	5	1/3	3	7	1	5	7	1	5	5	1/3	7	1	0.0818

Fig. 5 Rating of customers with respect to the negotiability level of payment for the order

Step 4: Calculation of overall weight:

Calculation the overall weight for each customer was done by multiplying the individual weights on each criteria with the weights of each criteria and adding them (Table 6).

For C1, overall weight = (0.097*0.0185) + (0.555*0.0380) + (0.097*0.1258) + (0.251*0.0191) = 0.0401.

Step 5: Prioritize the customers based on weight:

Once the weight for each customers were calculated, the weight were arranged in decreasing order and ranked accordingly for prioritization (Table 7).

6 Assign Customers to Route Based on Priority Rank:

This stage focuses on each customers being assigned routes based on priority rank.

For example, consider the clustered customers for vehicle V1. (Table 3). The set of customers are C6, C10, C11 and C15. Among the four customers, C11 has highest priority rank of 5 with weight 0.0887. Hence C11 is assigned first to the vehicle V1. Secondly, C6 has the second highest priority rank of 9 with weight of 0.0489. Thirdly, C10 has the third highest priority rank of 13 with weight 0.0328. At last, C15 has the least priority rank of 15 with weight 0.0213. Hence C15 is assigned last to the vehicle V1. Similarly assign all customers to the route based on priority rank and tabulate total distance and total load (Table 8).

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	W
C1	1	1/3	1/7	1/3	5	1/5	1	3	1/5	1/3	1/5	3	3	1/5	1	1/5	1/3	1/5	1	1/9	0.0191
C2	3	1	1/3	1	7	1	5	9	1	3	1	5	5	1	5	1/3	3	1	3	1/3	0.0597
C3	7	3	1	7	9	1	7	9	3	5	3	7	7	1	7	1	5	5	7	1	0.1262
C4	3	1	1/7	1	5	1	3	5	1/3	1	1/3	1	5	1/3	3	1/5	1	1/3	5	1/5	0.0361
C5	1/5	1/7	1/9	1/5	1	1/5	1/3	3	1/7	1/5	1/7	1/3	3	1/7	1/3	1/7	1/5	1/7	1/3	1/9	0.0105
C6	5	1	1	1	5	1	5	7	1	5	1	5	9	1	5	1/3	3	1	3	1/3	0.0684
C7	1	1/5	1/7	1/3	3	1/5	1	3	1/5	1/3	1/9	1	3	1/5	1	1/9	1/3	1/5	1	1/5	0.0159
C8	1/3	1/9	1/9	1/5	1/3	1/7	1/3	1	1/7	1/5	1/7	1/3	3	1/7	1	1/9	1/5	1/7	1/3	1/9	0.0093
C9	5	1	1/3	3	7	1	5	7	1	3	1	5	7	1	3	1/3	3	1	7	1/3	0.0654
C10	3	1/3	1/5	1	5	1/5	3	5	1/3	1	1/3	3	5	3	3	1/5	1	1	3	1/5	0.0414
C11	5	1	1/3	3	7	1	9	7	1	3	1	3	7	1	5	1/3	3	1	5	1/5	0.0657
C12	1/3	1/5	1/7	1	3	1/5	1	3	1/5	1/3	1/3	1	3	1/5	1	1/7	1/3	1/3	1	1/5	0.0174
C13	1/3	1/5	1/7	1/5	1/3	1/9	1/3	1/3	1/7	1/5	1/7	1/3	1	1/7	1/3	1/7	1/5	1/7	1	1/7	0.0088
C14	5	1	1	3	7	1	5	7	1	1/3	1	5	7	1	5	1/3	1	3	5	1/3	0.0682
C15	1	1/5	1/7	1/3	3	1/5	1	1	1/3	1/3	1/5	1	3	1/5	1	1/7	1/3	1/5	3	1/7	0.0168
C16	5	3	1	5	7	3	9	9	3	5	3	7	7	3	7	1	5	1	7	1	0.1241
C17	3	1/3	1/5	1	5	1/3	3	5	1/3	1	1/3	3	5	1	3	1/5	1	1/3	3	1/5	0.0346
C18	5	1	1/5	3	7	1	5	7	1	1	1	3	7	1/3	5	1	3	1	5	1/3	0.0628
C19	1	1/3	1/7	1/5	3	1/3	1	3	1/7	1/3	1/5	1	1	1/5	1/3	1/7	1/3	1/5	1	1/7	0.0148
C20	9	3	1	5	9	3	5	9	3	5	5	5	7	3	7	1	5	3	7	1	0.1338

Fig. 6 Rating of customers with respect to the level of trust between customer and company

Table 6 Overall weight for each customer

s.no	DC1 0.097	DC2 0.555	DC3 0.097	DC4 0.251	Overall Weight
C1	0.0185	0.0380	0.1258	0.0191	0.0401
C2	0.0432	0.0391	0.0388	0.0597	0.0446
C3	0.0185	0.1305	0.0101	0.1262	0.1061
C4	0.0432	0.0111	0.0207	0.0361	0.0215
C5	0.1648	0.0194	0.0846	0.0105	0.0382
C6	0.0911	0.0391	0.0122	0.0684	0.0489
C7	0.0185	0.0093	0.0389	0.0159	0.0148
C8	0.0432	0.0203	0.0173	0.0093	0.0195
C9	0.0432	0.0398	0.1328	0.0654	0.0558
C10	0.0911	0.0175	0.0372	0.0414	0.0328
C11	0.0093	0.1282	0.0090	0.0657	0.0887
C12	0.0432	0.0096	0.0725	0.0174	0.0212
C13	0.0093	0.0095	0.0214	0.0088	0.0104
C14	0.0185	0.1368	0.0099	0.0682	0.0951
C15	0.0432	0.0104	0.0714	0.0168	0.0213
C16	0.0432	0.1344	0.0198	0.1241	0.1112
C17	0.0093	0.0738	0.0377	0.0346	0.0539
C18	0.1381	0.0408	0.1462	0.0628	0.0665
C19	0.0185	0.0202	0.0108	0.0148	0.0177
C20	0.0911	0.0711	0.0818	0.1338	0.0898

Table 7 Prioritized customer list based on weight

Rank	Customer	Weight
1	C16	0.1112
2	C3	0.1061
3	C14	0.0951
4	C20	0.0898
5	C11	0.0887
6	C18	0.0665
7	C9	0.0558
8	C17	0.0539
9	C6	0.0489
10	C2	0.0446
11	C1	0.0401
12	C5	0.0382
13	C10	0.0328
14	C4	0.0215
15	C15	0.0213
16	C12	0.0212
17	C8	0.0195
18	C19	0.0177
19	C7	0.0148
20	C13	0.0104

Table 8 Prioritized route

Vehicle no	Prioritized route	Total distance (Kms)	Total load (Packets)
V1	Depot-C11-C6-C10-C15-Depot	359	78
V2	Depot-C16-C18-C4-C19-Depot	254	77
V3	Depot-C14-C17-C1-C7-Depot	354	67
V4	Depot-C20-C2-C5-C12-Depot	227	80
V5	Depot-C3-C9-C8-C13-Depot	112	74
Total		1306	

7 Results and Discussion

i. Impact on Transportation Distance:

The implementation of the proposed model showed reduction in transportation distance dramatically. Even though the distance travelled by V3 is little higher on new route, the overall distance was reduced from 1518 kms to 1306 kms which showcased a savings of 13.97% (Table 9).

ii. Impact on Customer Satisfaction:

After successful implementation, a survey was conducted by the experts to identify the customer satisfaction level for both

old and prioritized routes. The customers were asked to rate their satisfaction levels before and after implementation amongst different levels namely highly dissatisfied, dissatisfied, neutral, satisfied and highly satisfied. Customer satisfaction results of old route portrayed counts of 4, 5, 3, 3, 5 customers in Highly dissatisfied, Dissatisfied, Neutral, Satisfied and Highly Satisfied zones respectively. In comparison, the customer satisfaction results of the new route exhibited better counts of 0, 3, 5,00206 and 6 customers in Highly dissatisfied, Dissatisfied, Neutral,

Satisfied and Highly Satisfied zones respectively which proved a comprehensive rationalization of the research paper. (Table 10).

8 Conclusion

VRP forms an integral part of any supply chain and plays a significant role for productivity improvement in organisation through effective and efficient delivery of goods and services to customers. This research attempt has been exultant in terms of significant reduction in transportation distances and

Table 9 Comparison of old route and prioritized route

Vehicle no	Old Route		Prioritized Route		Improvement in %
	Route	Distance	Route	Distance	
V1	Depot-C10-C7-C1-C9-depot	401	Depot-C11-C6-C10-C15-Depot	359	+10.47%
V2	Depot-C13-C15-C11-C12-C3-depot	318	Depot-C16-C18-C4-C19-Depot	254	+20.12%
V3	Depot-C19-C14-C6-depot	348	Depot-C14-C17-C1-C7-Depot	354	-1.69%
V4	Depot-C8-C4-C16-C18-depot	262	Depot-C20-C2-C5-C12-Depot	227	+13.36%
V5	Depot-C5-C2-C20-C17-depot	189	Depot-C3-C9-C8-C13-Depot	112	+15.75%
TOTAL		1518		1306	+13.97%

Table 10 Comparison of customer satisfaction level between old and new route

	Old Route					New Route				
	Highly dissatisfied	dissatisfied	neutral	satisfied	Highly satisfied	Highly dissatisfied	dissatisfied	neutral	satisfied	Highly satisfied
C1			⊗						⊗	
C2			⊗						⊗	
C3	⊗									⊗
C4				⊗					⊗	
C5					⊗			⊗		
C6		⊗							⊗	
C7				⊗			⊗			
C8					⊗			⊗		
C9		⊗								⊗
C10					⊗			⊗		
C11			⊗							⊗
C12		⊗					⊗			
C13					⊗			⊗		
C14		⊗								⊗
C15				⊗				⊗		
C16	⊗									⊗
C17		⊗							⊗	
C18	⊗								⊗	
C19					⊗		⊗			
C20	⊗									⊗
total	4	5	3	3	5	0	3	5	6	6

simultaneously improved satisfaction levels of customers which will entice future researchers in this realm. When it comes to inimitability, the research initially encompasses the conventional Clarke and Wright's savings algorithm for customer clustering to solve the capacitated vehicle routing problem and later installs AHP for MCDM on assigning optimal routes to customers.

Nevertheless, it is apparent that companies are yet to leverage the vehicle routing for competitive advantage. In order to survive in this competitive market, firms should schedule the delivery of product based on scientific and optimised method. The consequence of poor planning are high transportation costs, delay in delivery leading to suppressed level of customer dissatisfaction. Effective routing and scheduling of vehicles are two important and difficult problems in transportation and logistics. Although minimizing total cost is an important criterion, for most logistic issues, criteria such as minimizing customer inconvenience and improving customer satisfaction plays a major role in long term success of any organisation involved in logistics.

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