A REVIEW OF DISRUPTION MANAGEMENT IN VEHICLE ROUTING PROBLEM (VRP), TRANSPORT DESIGN AND SCHEDULING

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Abstract: In the case of an unexpected occurrence, disruption management is a method of rescheduling activities and it has been used in a variety of fields, including organized carrier scheduling and project management. The purpose of this review is to examine Ant Colony Optimization (ACO), the problems of Heuristics for Delivery Waste Collection (VRP), ARC Routing, Node Routing, and Container/skip. Other issues and problems examined in the paper were Non-Skip, Algorithms for the VRP, Improvement Algorithms, Simulated Annealing, and ACO for Capacitated Vehicle Routing, Clustering Analysis, and Probabilistic-D Cluster Analysis. It covers the fundamental characteristics of disruption management as well as the related goals and kinds of disruption that may occur in this setting. The various formulations and solution techniques are discussed in facet. A collection of relevant articles has been summarized and categorized according to the kind of disruption problem being addressed, the relevant goals, and the solution method used to resolve the problem. Vehicles must be emptied at a trash disposal facility before they may be used to collect garbage from further clients. The growing amount of solid waste generated as a result of population expansion is one of the primary reasons why this issue has emerged as a significant review priority.

Keywords: Routing Problem, waste collection, disruption management, carriers

1. INTRODUCTION

A review of Vehicle Routing Problem (VRP), ant heuristics and examples of heuristic techniques that have been used to solve the Vehicle Routing Problem (VRP) for deliveries are presented. This is followed by some literature on VRP on solid waste collection, which includes previous research work dealing with solid waste collection such as arc routing, and node routing, particularly skip problems and non-skip problems. The vehicle routing problem (VRP) deals with the optimal assignment of a set of transportation orders to a fleet of vehicles and the sequencing of stops for each vehicle. The VRP was first introduced by Alves and Climaco (2007) and was developed by Baldacci et al., (2004). The main objective of the VRP is to minimize the distribution costs for the individual carriers, and can be described as the problem of assigning a collection of routes from a depot to a number of geographically distributed customers, subject to certain constraints.

A formal definition of disruption management can be found in Baldacci et al., (2004) "At the beginning of a business cycle, an optimal or near-optimal operational plan is obtained by using certain optimization models and solution schemes. When such an operational plan is executed, disruptions may occur from time to time caused by internal and external uncertain factors. As a result, the original operational plan may not remain optimal, or even feasible. Consequently, we need to dynamically revise the original plan and obtain a new one that reflects the constraints and objectives of the evolved environment while minimising the negative impact of the disruption. This process is referred to as disruption management." This review focusses on the use of disruption management in vehicle routing and scheduling applied to road freight distribution. The paper then focuses on one type of such problem, in which a vehicle breaks down during the

delivery and a new routing solution needs to be quickly generated to minimize the costs.

2. ANT COLONY OPTIMIZATION (ACO)

Ant Colony Optimization is one of the most recent Meta heuristic for the application to CO problems. The basic ideas of ACO were introduced in Marco Dorigo, (1992) and successively extended in Dorigo et al. (1999). In this section we present the description of ACO given in Dorigo and Di Caro (1999). The ACO was motivated by the foraging behavior of real ants. This behavior as described by Bektaş et al., (2014) enables ants to find the shortest paths between food sources and their nest. Initially, ants explore the area surrounding their nest in a random manner. As soon as an ant finds a source of food, it evaluates the quantity and quality of the food and carries some of this food to the nest. During the return trip, the ant deposits a pheromone trail on the ground. The quantity of pheromone deposited, which may depend on the quantity and quality of the food, will guide other ants to the food source. The indirect communication between the ants via the pheromone trails allows them to find the shortest path between their nest and food sources. This functionality of real ant colonies is exploited in artificial ant colonies in order to solve CO problems.

In ACO algorithms, the pheromone trails are simulated via a parameterized probabilistic model that is called the pheromone model. The pheromone model consists of a set of model parameters whose values are called the pheromone values. The basic ingredient of ACO algorithm is a constructive heuristic that is used for probabilistically constructing solutions using the pheromone values.

In general, the ACO approach attempts to solve a CO problem by iterating the following two steps:

- ❖ Solutions are constructed using a pheromone model, that is, a parameterized probability distribution over the solution space.
- ❖ The solutions that were constructed in earlier iterations are used to modify the pheromone values in a way that is deemed to bias the search toward high quality solutions.

3. HEURISTICS FOR DELIVERY PROBLEMS

Basically, the VRP for delivery problems can be defined as delivering goods to a number of customers who have placed orders for a certain quantity of these goods from a central depot. Due to some constraints such as load, distance and time, a single vehicle may not be able to serve all the customers. The problem then is to determine the number of vehicles needed to serve the customers as well as the routes

that will minimize the total distance travelled by the vehicles. Many heuristics have been introduced in the literature for searching for good solutions to the problem. For instance, the savings algorithm of Clarke and Wright (1964), the sweep algorithm of Branké et al., (eds) (2008), the cluster-first, route-second heuristic of Fisher and Jaikumar (1981), the path scanning heuristic of Golden et al., (2016), and the route-first, cluster-second heuristic of Clausen et al., (2019).

Many papers in the literature deal with academic test problems. Examples of real-life delivery problems that catch the attention of researchers are newspaper delivery (e.g., Boonkleaw et al., (2009); Russell et al., (2008); Song et al., (2002); Ree and Yoon, (1996), food delivery (e.g., Chen et al., (2009); Rusdiansyah and Tsao, (2005); Faulin, (2003), as well as postal and parcel delivery (e.g. Bruns et al., (2000); Novaes and Gracioli, (1999).

4. WASTE COLLECTION PROBLEM

Dealing with waste collection problem is different from the collection problem as discussed in the previous section. There is an additional constraint that needs to be considered in solving this problem. Instead of returning to the depot to unload the collected goods, in waste collection problem vehicles need to be emptied at a disposal facility before continuing collecting waste from other customers. Thus, multiple trips to the disposal facility occur in this problem before the vehicles return to the depot empty, with zero waste. A complication in the problem arises when more than one disposal facilities are involved. Here one needs to determine the right time to empty the vehicles as well as to choose the best disposal facility they should go to so that the total distance can be minimized. For example, it may not be optimal to allow the collection vehicle to become full before visiting a disposal facility. Increasing quantities of solid waste due to population growth, especially in urban areas, and the high cost of its collection are the main reasons why this problem has become an important research area in the field of vehicle routing. In the next two sections, previous work dealing with waste collection as arc routing problems and as node routing problems are reviewed (Dhahri et al., (2013).

5. ARC ROUTING PROBLEMS

Due to the large number of residential waste locations that have to be collected from this collection problem is often dealt with as an arc routing problem, whereas the collection of commercial waste is dealt with as a node routing problem. In this section some of the previous work dealing with arc routing problems for waste collection is reviewed. Dhahri, et al., (2013) applied a revised multi-objective mixed-integer programming model (MIP) for analyzing the optimal path in

a waste collection network within a geographic information system (GIS) environment. They demonstrated the integration of the MIP and the GIS for the management of solid waste in Kaohsiung, Taiwan. Computational results of three cases particularly the current scenario; proposed management scenario (without resource equity consideration) and modified management scenario (with resource equity requirement) are reported. Both the proposed and the modified management scenarios show solutions of similar quality. On average both scenarios show a reduction of around 36.46% in distance travelled and 6.03% in collection time compared to the current scenario. Ernst et al., (2007) solved a capacitated arc routing problem (CARP) with side constraints for a refuse collection Vehicle Routing Problem (VRP) using two lower-bounding methods to incorporate the side constraints and a three-phase heuristic to generate a near optimal solution from the solution obtained with the first lower-bounding method. Then, the feasible solution from the heuristic represents an upper bound to the problem. The heuristic they developed is a route-first, cluster-second method. Freling et al., (2001) presented an ant algorithm for designing collection routes for urban waste. To ascertain the quality of the algorithm, they tested it on three instances from the capacitated arc routing problem literature i.e., Golden et al., (1983); Benavent et al. 1992 and Li and Eglese, (1996) and also on a set of real-life instances from the municipality of Sant Boi del Llobregat, Barcelona, Spain. The characteristics of each dataset were presented. Computational results for Golden et al., (1983) and Benavent et al. (1992) are within less than 4% of the best-known solution, and for Li and Eglese, (1996) dataset up to 5.08%.

Hu and Sun (2012) presented a heuristic method for a mixed CARP, inspired by the refuse collection problem in Lisbon, Portugal. The proposed heuristic can be used for directed and mixed cases. Mixed cases indicate that waste may be collected on both sides of the road at the same time (i.e., narrow street), whereas waste for the directed cases only can be collected on one side of the road. The authors reported computational results for the directed case on randomly generated data and for the mixed case on the extended CARP benchmark problems of Jiang et al., (2013). Computational results for the directed problem, involving up to 400 nodes show the gap values (between their lower bound and upper bound values computed from their heuristic method) varying between 0.8% and 3%. For the mixed problem, comparison results with four other heuristics namely, extended Path-Scanning, extended Ulusoy's, extended Augment-Merge and extended Merge are reported. They stated that they were able to get good feasible solutions with gap values (between the lower

bound values obtained from Jozefowicz et al., (2008) and their upper bound values) between 0.28% and 5.47%.

Jozefowicz et al., (2008) solved a solid waste collection in Porto Alegre, Brazil which involved 150 neighborhoods, with a population of more than 1.3 million. They designed a truck schedule operation plan with the purpose of minimizing the operating and fixed truck costs. In this problem, the collected waste was discarded at recycling facilities, instead of disposal facilities. Furthermore, the heuristic approach used in this problem also attempted to balance the number of trips between eight recycling facilities to guarantee the jobs of poor people in the different areas of the city who work at the recycling facilities. Computational results indicate that they reduce the average number of vehicles used and the average distance travelled, resulting in a saving of around 25.24% and 27.21%, respectively. Letchford et al., (2007) proposed two-phase heuristics and one best insertion method for solving a sectoring arc routing problem (SARC) in a municipal waste collection. In SARC, the street network was partitioned into a number of sectors, and then a set of vehicle trips was built in each sector that aimed to minimize the total duration of the trips. Moreover, workload balance, route compactness and contiguity were also taken into consideration in the proposed heuristics.

Li et al., (2007a) proposed a heuristic procedure which consisted of a route first, cluster second method for solving a solid waste collection problem in Onitsha, Nigeria. Comparison of the results with the existing situation showed that they used one less collection vehicle, a reduction of 16.31% in route length, a saving of around 25.24% in collection cost and a reduction of 23.51% in collection time. In some cases, waste collection problems are solved as node and arc routing problems. For example, Li et al., (2007a) transformed the arc routing into a node routing problem due to the road constraint such as forbidden turns for solving an urban waste collection problem in the municipality of Sant Boi de Llobregat, Barcelona, Spain with 73,917 inhabitants using an ant colonies heuristic, which was based on nearest neighbour and nearest insertion methods. Computational results showed that both methods produced less total distance compared with the current routes. In particular, routes from nearest neighbour and nearest insertion travelled 35% and 37% less, respectively.

Furthermore, Li et al., (2007b) presented a spatial decision support system (SDSS) to generate vehicle routes for multi-vehicle routing problems that served demand located along arcs and nodes of the transportation network. This was mainly due to some streets which were too narrow for

standard-sized vehicles to traverse, thus the demand along arcs as well as at network nodes were required for solving waste collection in Coimbra, Portugal.

6. NODE ROUTING PROBLEMS

If the location of every collection point is known when solving the waste collection problem then it is a node routing problem. Vehicles will travel from the depot to a customer and then to another customer, etc. to collect waste based on the sequence of visits on the vehicle route. This sequence includes trips to disposal facilities to empty the vehicle and the last visit would be the depot. In the next section, previous work dealing with node routing problems, particularly the skip problems and non-skip problems are reviewed. It should be noted here that Li et al., (2008) has discussed the importance attached to waste management and collection in terms of the green logistics agenda.

7. CONTAINER/SKIP PROBLEMS

Li et al., (2008) dealt with the problem of delivering empty skips and collecting full skips from customers. Vehicles can carry only one skip at a time, but skips can be of different types. They stated that the problem was first considered by Li et al., (2009b) Their solution approach was based on two simple heuristics and an enumerative approach. They reported computational experience with randomly generated problems involving up to 160 customers and a real-world problem involving 30 customers. Lust and Teghem (2019) considered a sanitation routing problem they called the roll on-roll off vehicle routing problem. In this problem trailers, in which waste was collected, were positioned at the customers. A tractor (vehicle) could move only a single trailer at a time. Tractor trips involved, for example, moving an empty trailer from the disposal facility to a customer and collecting the full trailer from the customer. A key aspect of their work was that they assumed that the set of trips to be operated was known in advance (so the problem was reduced to deciding for these trips how they would be serviced by the tractors (Mamasis et al., (2013).

They presented four heuristic algorithms and gave computational results for problems involving up to 199 trips and a single disposal facility. Li et al., (2009a) developed a heuristic algorithm called SMART-COLL for a problem motivated by waste collection in Brescia, Italy. In their problem skips were collected from customers and the vehicle could carry only one skip at a time. They called the problem the 1-skip collection problem. They considered skips of different types and time windows were imposed on both the customers and the disposal facilities. Computational

experience was reported for real world data involving 51 customers and 13 disposal facilities.

Marler and Arora (2004) developed a three-phase heuristic technique to create collection routes for the collection of urban recyclable waste in the central region of Portugal. Three types of waste in separate containers must be collected individually. The collected containers were emptied at two central depots and vehicles started and terminated a route in one of these depots. Computational results showed that the total distance travelled of the proposed solution was 29% less than the historical distance. Baldacci et al. (2006) dealt with an extension of the problem considered by Bodin et al (2000). They considered multiple disposal facilities as well as inventory facilities at which empty trailers were available. They presented an approach based on regarding the problem as a time constrained vehicle routing problem on a directed multi-graph. Computational results for problems involving up to 75 customers and two disposal facilities were presented.

Le Blanc et al. (2006) presented a paper dealing with the collection of containers from end-of-life vehicle dismantlers in the Netherlands. In the problem they that considered the vehicles could carry two containers at a time. Their heuristic was a two-step procedure, first generating candidate routes, then selecting from these routes using a set partitioning approach. They reported potential cost savings of over 18% compared with the current system. Even though Aringhieri et al. (2004) solved a skip problem in Perugia, Italy, they solved the problem as an arc routing problem due to the different types of containers used to collect different waste. Therefore, the selected arcs for the vehicle to travel depend on the service requests which are characterized by types of waste, container and the collection point.

8. NON-SKIP PROBLEMS

The majority of papers in the literature for non-skip problems are case study papers, focusing on results obtained when algorithms are applied to real world data. Only a few of these papers report computational experience with publicly available waste collection test instances. Marler and Arora (2004) presented a real-life comparative study between a revised heuristic algorithm and an optimization technique particularly, minimum spanning tree and integer programming model, for investigating the effectiveness of vehicle routing and scheduling in a solid waste collection system. To illustrate the comparison of both techniques, a case study in the city of Kaohsiung, Taiwan which involved 854 collection points was presented. As expected in terms of cost-saving perspective, a set of near-optimal solutions from

the heuristic algorithm were not as economic as the optimal solutions from the optimization scheme. Computational results showed that the total number of collection vehicles and the crews needed for the optimal solutions were 14 and 56, respectively whereas, the heuristic solutions required 22 vehicles and 84 crews in total. However, in terms of total routing distance and collection time, the heuristic solutions showed reductions of 12.7% and 0.9%, respectively even though they required more vehicles. Moreover, the authors stated that the heuristic algorithms allowed the analysis of a much larger service area of interest within the same computational time compared to the performance of an optimization model. In their view, if an improvement in high performance computing comes into reality in the future it may overcome the present computational limitation of the optimization model.

Marler and Arora J (2004) proposed a heuristic procedure to solve a waste collection problem in Hanoi, Vietnam. In their problem there were time windows associated with collection from customers and their heuristic first constructed routes based on an approach developed by Solomon (1987) and then improved them. They reported computational experience indicating that they could achieve an operating cost saving of 4.6% when compared with the current situation. Angelelli and Speranza (2002a) presented an algorithm based on tabu search for the periodic version of the problem where routes must be designed over a planning horizon of more than one time period so as to meet customer service requirements. Their approach was based on the tabu search algorithm for vehicle routing of Marler and Arora (2004). Computational results were presented for problems involving two and six days in the planning horizon. Angelelli and Speranza (2002b) proposed a model that fits three different waste collection systems to estimate operational costs. Their solution procedure was based on Angelelli and Speranza (2002a) and the results were presented relating to two case studies in Val Trompia, Italy and Antwerp, Belgium.

Marler and Arora (2004) reported how they developed a system called Waste Route to reduce operating costs for a large company involved in waste collection. They gave one example of an area that went from ten routes to nine, improving route productivity (as measured by the amount collected per hour) by some 11%. The heuristic used for the Waste Route system of Sahoo et al. (2005) is fully described in Kim et al (2006). Customers had time windows for collection, and there were multiple disposal facilities, as well as a driver rest period. They extended Solomon's (1987) insertion heuristic to cope with both multiple disposal

facility visits and the driver rest period and used it to construct routes, which were improved using simulated annealing and a local search exchange procedure called CROSS (Taillard et al. 1997). As their work was motivated by the practical context reported in Sahoo et al (2005), they discussed a number of issues with solutions produced by this heuristic: route compactness, workload balancing and computation time. In order to deal with these issues they also presented a heuristic based on capacitated clustering that generates clusters based on the estimated number of vehicles required, and then routes customers within each cluster. Computational results were presented for ten problem instances, derived from real-world data, involving up to 2100 customers that the authors made publicly available.

Minis et al., (2012) used a mixed integer programming model (MIP) to optimize the routing system for Deir Al-Balah, Gaza Strip. The problem involved 58 pick-up points, one disposal facility and three collection vehicles. Comparison of the results with the existing routing system were presented in terms of the total distance travelled. The result showed that the solution involved 23.4% less compared to the existing distance. Thus, the monthly cost could be reduced by approximately US\$1140. They also combined both skip and non-skip problems to determine the minimum cost/distance efficient collection paths for transporting solid waste to the landfill for the Asansol Municipality Corporation (AMC) of West Bengal State, India. In total, the problem involved 1405 collection bins with three different sizes. Three types of vehicles were used for the collection of these bins. The vehicle type-A and the vehicle type-B served as skip and non-skip problems, respectively. The vehicle type-C collected the waste from C-type bins and disposed the waste at its nearest A-type bin. The vehicle would repeat the process until all the waste from C-type bins was collected. Then the vehicle would return to the garage from the location of the last A-type bin served. No comparison with the routing system practiced by AMC was made. However, they compared the current annual operating cost AMC was spending with their estimated operating cost with respect to the proposed solution. Comparison of the results indicated that AMC could save about 66.8% every year if the proposed solution was applied.

Minis et al., (2012) applied classical MIP for a case study in Turkey for transporting metal waste from 17 factor, The monthly cost of the proposed optimal solution was approximately \$48000. Comparison of the routes with those currently being practiced was not presented. Data were

provided by TOSB (TAYSAD Organized Industrial Region) where TAYSAD was an abbreviation of Association of Automotive Parts & Components Manufacturers. Nuortio et al. (2006) considered a problem based on waste collection in two regions of Eastern Finland. Their problem included time windows and they solved the problem using Guided Variable Neighborhood Thresholding (Kytöjoki et al. 2007).

Apaydin and Gonullu (2007) used Route View ProTM software for constructing waste collection route in Trabzon, Turkey. The collection involved 777 containers and one disposal site. The solution was compared with the present routes in terms of the total route distances, travelling time as well as the monthly cost. Comparison of the results indicated that their routes outperform the present. Both distance and travelling time were reduced by up to 59% and 67%, respectively whilst the monthly cost was decreased by up to 24.7%. Karadimas et al., (2007) presented an ant colony system (ACS) for determining waste collection routes for the Municipality of Athens (MoA). The collection involved 72 loading spots. Comparison of the results with the empirical method (Kollias, 1993) used by MoA were presented. The route length of the empirical model was 9850, whilst the ACS route was 7328. Thus, the improvement was approximately 25.6%.

Ombuki-Berman et al. (2007) presented a multi-objective genetic algorithm that used a crossover procedure (Best Cost Route Crossover) from Ombuki et al. (2006). They reported results from their approach using the test problems of Kim et al (2006), but no computation times were given. Alagöz and Kocasoy (2008) considered health waste collection in Istanbul. They used a commercial vehicle routing package to consider a number of scenarios relating to the type of facility used for waste disposal. McLeod and Cherrett (2008) considered a problem relating to waste collection in the UK. They used a commercial vehicle routing package and reported that vehicle mileage could be reduced by up to 14%.

Mu and Eglese (2013) proposed several heuristic algorithms for a routing problem of a Belgian company collecting waste at slaughterhouses, butchers and supermarket. The company was responsible for collecting high-risk and low-risk waste categories of animal waste. Both wastes needed to be collected separately. The instances could be found at <http://www.econ.kuleuven.ac.be/public/N05012/>. Comparison of the results in terms of the total travelling time between the proposed solutions and the current routes were presented. For the low-risk waste, the results indicated that the current total travelling time could be reduced by up to

15.5%, whereas the travelling time for the collection of high-risk waste could be reduced by up to 9%. Komilis (2008) presented two mixed integer-linear programming models particularly time based optimization model and cost optimization model for the waste collection problem in Athens. The waste was collected from the source nodes and taken to potential intermediate nodes, namely waste production nodes (WPN) and waste transfer stations (WTS), respectively and finally to the landfill as a sink node. The cost modeling approach used in this work had similarities with the cost optimization model used in Mu and Eglese (2013), particularly in calculating fuel and maintenance costs as well as labour cost. The problem involved seven WPN, three WTS and one landfill. However, WTS may or may not be included in the optimal path, depending on the solution.

Mu et al., (2011) proposed a methodology for designing an efficient urban waste collection for the west-central zone of the Municipality of Santiago using a combination of mathematical modeling such as linear integer programming and a tabu search algorithm in a GIS environment. The collection involved 1600 bins and the comparison of the results indicated that the proposed routing system reduced 50% of current monthly cost spent on waste collection system with a reduction of 57% in the number of vehicles as well as a reduction of 57% in the number of workers needed to complete the collection. Chalkias and Lasaridi (2009) used ArcGIS Network Analyst in their work for the waste collection in the Municipality of Nikea (MoN), Athens, Greece. The problem involved 501 collection bins and one disposal site. Besides constructing collection routes, replacing and reallocating the waste collection bins was also taken into consideration. These two scenarios were compared with the current routes. Computational results demonstrated that both scenarios provided savings in terms of collection time and total travel distance. The first scenario (constructing routes with the current location of the waste bins) saved around 3.0% in collection time and 5.5% in distance travelled, whereas the second scenario (constructing routes after replacing and reallocating the waste bins) saved around 17.0% in collection time and 12.5% in distance travelled.

Hemmelmayr et al. (2009) presented a paper motivated by a real world waste collection problem. They considered a periodic problem, where routes must be designed over a multi-day planning horizon so as to meet customer service requirements. They considered a number of constraints motivated by their underlying application and in particular in their application the vehicle needed not return to the

depot empty. They used dynamic programming to sequence disposal facility visits within a variable neighborhood search approach. Computational results were presented for instances, involving up to 288 customers, derived from vehicle routing problems given in the literature. Repoussis et al. (2009) considered waste oil collection and recycling in Greece. In their problem, vehicles were compartmentalised and they used a list based threshold accepting metaheuristic (Tarantilis et al. 2004) to design vehicle routes. They reported reductions of up to 30% in the cost per unit of waste collected.

Zamorano et al. (2009) attempted to reduce the waste collection management costs in Churriana de la Vega, Spain. The objective included reducing fuel consumption by minimizing the travel time of the collection routes using ArcGIS Network Analyst. Computational results showed reductions of 32.3% in travelling time compared to the current routes. Other literature focusing on minimizing fuel consumption are Tavares et al. (2008) and Tavares et al. (2009). Reference could be made of some of the previous work dealing with waste collection but where no disposal facilities were involved (Mu et al., 2011).

9. ALGORITHMS FOR THE VRP

Since the VRP is an NP-hard problem, many approximation algorithms have been proposed in the literature. These algorithms can be classified into two main groups:

- a. Construction algorithms
- b. Improvement algorithms

Construction Algorithms

Construction algorithms are used to build an initial feasible solution for the problem. They build a feasible solution by inserting unrouted customers iteratively into current partial routes according to some specific criteria, such as minimum additional distance or maximum savings, until the route's scarce resources (e.g., capacity) are depleted Cordeau et al. (1999). These types of algorithms are classified as either sequential or parallel algorithms. In sequential algorithm routes are built one at a time whereas in a parallel algorithm many routes are constructed simultaneously.

Sequential Construction Algorithms

Sequential construction algorithms are mostly based on the Sweep Heuristic Gillet and Miller, (1974) and the Savings Heuristic Clarke and Wright, (1964). In the sweep heuristic, routes are constructed as an angle sweeps the location of nodes on a 2D space. In the savings heuristic, first routes are constructed in a predefined quantity and then new nodes are

added to available nodes in order to obtain maximum savings. Baker and Schaffer (1986) proposed the first sequential construction algorithm. The algorithm is based on savings heuristic and starts with all possible single customer routes in the form of depot – i – depot. Then two routes with the maximum saving are combined at each iteration. The saving between customers i and j is calculated as

$$S_{ij} = d_{i0} + d_{0j} - Gd_{ij}$$

Where G is the route form factor and d_{ij} is the distance between node

Solomon (1987) proposed Time Oriented Nearest Neighborhood Heuristic. Every route is initialized with the customer closest to the depot. At each iteration unassigned customer that is closest to the last customer is added to the end of the route. When there is no feasible customer, a new route is initialized. Solomon, (1987) also proposed Time-Oriented Sweep Heuristic. First, customers are assigned to different clusters and then TSPTW problem is solved using the heuristics proposed by Savelsbergh, (1985).

Parallel Construction Algorithms

Solomon (1987) proposed a Giant-Tour Heuristic. In this heuristic, first of all, a giant route is generated as a travelling salesman tour without considering capacity and time windows. Then, it is divided into number of routes. Potvin and Rousseau, (1993) proposed parallelization of the Insertion Heuristics. Each route is initialized by selecting the farthest customer from the depot as a centre customer. Then, the best feasible insertion place for each not yet visited customer is computed. Customers with the largest difference between the best and the second-best insertion place are inserted to the best feasible insertion place. Parallel algorithm in Foisy and Potvin, (1993) also constructs routes simultaneously using the Insertion Heuristics to generate the initial center customers. Antes and Derigs, (1995) proposed another parallel algorithm based on the Solomon's heuristic. Offers comes to the customers from the routes, unrouted customers send a proposal to the route with the best offer, and each route accepts the best proposal.

Improvement Algorithms

Improvement algorithms try to find an improved solution starting from a considerably poorer solution. Almost all improvement algorithms for the VRP use an exchange neighborhood to obtain a better solution. Exchange of neighbourhood can be intra or inter route (Thangian and Petrovic, 1998). While k-opt, procedure operates within a route, the relocate, exchange, and cross operators operate

between routes. Croes, (1958) introduced k-opt approach for single vehicle routes. In this heuristic, a set of links in the route are replaced by another set of k links. The Or-Opt exchange originally proposed for TSP by Or, (1976) removes a chain of at most three consecutive customers from the route and tries to insert this chain at all feasible locations in the routes. In 1-1 exchange procedure connectors between nodes are replaced by connectors between nodes either in the same or in different route. 1-0 exchange move transfers a node from its current position to another position in either the same or a different route.

Mu et al., (2011) proposed the k-node interchange for the first time to take time windows into account. In this heuristic, sets M_1 and M_2 are identified for each customer i and its successor j . M_1 Denotes two customers that are closest to i and j on a different route than i and j . The elements of the sets M_1 and M_2 are removed and inserted in any other possible way. Osman and Christofides (1994) introduced λ -interchange local search that is a generalization of the relocate procedure λ , the parameter, denotes the maximum number of customer nodes that can be interchanged between routes. Potvin and Rousseau, (1995) present two variants of 2-Opt and Or-Opt. For the 2-Opt, they proposed the consideration of every pair of links in different routes for removal. For the Or-Opt, every sequence of three customers is considered and all insertion places are also considered for each sequence. Schulze and Fahle, (1999) proposed shift-sequence algorithm. A customer is moved from one route to another checking all possible insertion positions. If an insertion is feasible after the removal of another customer, that customer is removed.

10. META HEURISTICS

In order to escape local optimal and enlarge the search space, meta heuristic algorithms such as simulated annealing, tabu search, genetic algorithm, and ant colony algorithm have been used to solve the VRP (Mu et al., 2011).

Simulated Annealing

Simulated Annealing (SA) is a stochastic relaxation technique. It is based on the annealing process of solids, where a solid is heated to a high temperature and gradually cooled in order to crystallize (Bräysy and Gendreau, 2001). During the SA search process, the temperature is gradually lowered. At each step of the process, a new state of the system is reached. If the energy of the new state is lower than the current state, the new solution is accepted. But if the energy of the new state is higher, it is accepted with a certain probability. This probability is determined by the temperature. SA continues searching the set of all possible solutions until a stopping criterion is reached.

Mu et al., (2011) used λ -interchange with $\lambda=2$ to define the neighborhood and decrease the temperature after each iteration. In case the entire neighborhood has been explored without finding and accepting moves the temperature is increased. Chiang and Russell (1996) proposed three different SA methods. First one uses modified version of the k-node interchange mechanism and second uses λ -interchange with $\lambda=1$. The third is based on the concept of tabu list of Tabu Search. Tan et al. (2001) proposed an SA heuristic. They defined a new cooling schedule. Thus, when the temperature is high, the probability of accepting the worse is high, when the temperature is decreased according to function given above; the probability of accepting worse is reduced. Finally, Li and Lim, (2003) proposed an algorithm that finds an initial solution using Solomon 's insertion heuristic and then starts local search from initial solution using proposed tabu-embedded simulated annealing approach.

Tabu Search

Tabu search (TS) presented by Glover (1986) is a memory based local search heuristic. In TS, the solution space is searched by moving from a solution s to the best solution in its neighbourhood $N(s)$ at each iteration. In order to avoid from a local optimum, the procedure does not terminate at the first local optimum and the solution may be deteriorated at the following iteration. The best solution in the neighbourhood is selected as the new solution even if it is poorer. Solutions having the same attributes with the previously searched solutions are put into tabu list and moving to these solutions is forbidden. This usually prevents making a move to solutions obtained in the last t iterations. TS can be terminated after a constant number of iterations without any improvement of the overall best solution or a constant number of iterations.

Garcia et al. (1994) applied TS to solve VRP for the first time. They generated an initial solution using Solomon 's insertion heuristic and search the neighbourhood using 2-opt and Or-opt. Garcia et al. (1994) also parallelized the TS using partitioning strategy. One processor is used for controlling the TS while the other is used for searching the neighbourhood. Thangiah et al. (1994) proposed TS with λ -interchange improvement method. They also combined TS with SA to accept or reject a solution. Potvin et al. (1995) proposed an approach similar to Garcia et al. (1994) based on the local search method of Potvin and Rousseau, (1995). Badeau et al. (1997) generated a series of initial solutions. Then, they decomposed them into groups of routes and performed TS for each group using the exchange operator.

Genetic Algorithm

The Genetic Algorithm (GA) is based on the Darwinian concept of evolution. Solutions to a problem are encoded as chromosomes and based on their fitness; good properties of solutions are propagated to a next generation (Vacic and Sobh, 2002). The creation of the next generations involves four major phases:

1. Representation: The significant features of each individual in the population are encoded as a chromosome.
2. Selection: Two parent chromosomes are selected from the population.
3. Reproduction: Genetic information of selected parents is combined by crossover and two offspring of the next generation are generated.
4. Mutation: The gene sequence of small number of newly obtained is randomly swapped. A new generation is created by repeating the selection, reproduction, and mutation phases until a specified set of new chromosomes have been created. Then the current population is set to the new population of chromosomes.

Thangiah et al. (1991) applied the GA to VRP for the first time. GA is proposed to find good clusters of customers. The routes within each cluster are then constructed with a cheapest insertion heuristic and λ -interchange is applied. Thangiah et al. (1995) generated initial population by clustering the customers randomly into groups and applying the cheapest insertion heuristic for each group. Then, 2-point crossover was used. GA of Potvin and Bengio, (1996) is performed on chromosomes of feasible solutions. Parents are randomly selected and two types of crossovers are applied to these parents. The reduction of routes is obtained by two mutation operators. The routes are improved using Or-Opt at every k iteration Amponsah and Darkwah (2005) showed that real life problem are difficult to solve by exact algorithms that find optimal solutions in finite number of steps. Hence, the need for heuristics methods such as Genetic Algorithm (GA) and Ant Colony Optimization (ACO). Simulated Annealing (SA) and Tabu Search(TS) are all pair-wise local search algorithms that search the neighbourhood of current solution to find the next solution.

ACO for Capacitated Vehicle Routing Problem

Bullneheimer et al. (1998) applied the AS to the VRP with one central depot and identical vehicles for the first time. They set the number of ants (m) equal to the number of cities (n). Initially, each ant is placed at each customer. Then, the ants constructed vehicle routes by successively selecting cities,

until all cities have been visited. When there is no feasible city to visit, the depot is selected and a new route is started. City j is selected after city i according to the random-proportional rule:

$$P_{ij}^k = \frac{(\tau_{ij})^\alpha (n_{ij})^\beta (\mu_{ij})^\gamma (k_{ij})^a}{(\tau_{ij})^\alpha (n_{ij})^\beta (\mu_{ij})^\gamma (k_{ij})^a}$$

$n_{ij} = \frac{1}{d_{ij}}$: Saving of visiting customer j after customer i

$\mu_{ij} = d_{io} + d_{oj} - d_{ij}$

k_{ij} : Capacity utilization through the visit of customer

$$k_{ij} = \frac{Q_i + q_j}{Q}$$

Q_i = Total capacity use including the capacity requirement of customer i

Y : Relative influence of the savings

Relative influence of k_{ij}

After routes are constructed using the proposed approach, 2-opt heuristic is applied to each route. Then, pheromone trail on arc (i, j) is updated according to:

If arc (i, j) is used by the k-th ant, the pheromone trail on that are increased by $\Delta_{ij}^k = \frac{1}{L_k}$. In addition, if arc (i, j) is on the so far best route, it is emphasized as if σ elitist ants used it. Each Elitist ant increases the pheromone trail by $\Delta_{ij}^* = \frac{1}{L_s}$.

STEP I: Initialize

STEP II: For $I^{\max}$ iterations do

For each ant $k=1, \dots, m$ generate a new solution

Improve all vehicle routes using the 2-opt heuristic

Update the pheromone trial

Figure 2.0 A skeleton ACO algorithm applied to CVRP

Bullneheimer et al. (1999) introduced an improved ACO algorithm for the VRP with one central depot and identical vehicles. Differences of this approach from Bullneheimer et al. (1998) are in random proportional rule and pheromone trail update.

However, following parametrical savings function is used for the visibility:

$$\eta_{ij} = d_{io} + d_{oj} - g d_{ij} + f | d_{io} - d_{jo} | = s_{ij} - (g-1)d_{ij} + f | d_{io} - d_{jo} |$$

After an artificial ant has constructed a feasible solution; ants are ranked according to solution quality. Only the best ranked and elitist ants are used to update the pheromone trails. This update is done using equation $\tau_{ij} = \rho \tau_{ij} + \Delta \tau_{ij} + \Delta \tau_{ij}^*$.

They also used candidate lists for the selection of customers. Candidate lists are formed using nearest neighborhood.

Bell and McMullen (2003) used ant colonies to solve the CVRP. Differences of this approach from Bullneheimer et al. (1998) are in selection the next customer and pheromone trail update. Candidate lists are also formed using nearest neighbourhood. Selection of the next customer j is made using ACS approach. Thus, using equations

$$p_{ij}^k = \begin{cases} \max_{\text{allowed}} \left\{ \tau_{ij} \cdot [\eta_{ij}]^\beta \right\}, & \text{if } q \leq q_0 \\ p_{ij}^k, & \text{otherwise} \end{cases}$$

where q is a random variable uniformly distributed over $[0,1]$ and $q_0 \in [0,1]$ is a parameter and

Each ant may either follow the most favourable path or randomly select a path to follow based on a probability distribution. Trail updating includes local updating of trails after each selection and global updating of the best solution route after all routes are constructed.

Doerner et al. (2001) proposed the savings-based ant system approach (SbAS). The basic structure is identical to Bullneheimer et al. (1999), but they use the savings algorithm to calculate visibility.

The attractiveness is calculated by: $\varepsilon_{ij} = (s_{ij})^\beta (\tau_{ij})^\alpha$. Where s_{ij} is the savings of visiting customer j after customer i .

Initially attractiveness values are sorted in non-increasing order and k -best combinations are considered at each decision step. If allowed k denotes the set of k feasible combinations (i, j)

After solutions are constructed, only the best ranked and elitist ants are used to update the pheromone trails.

11. CLUSTERING ANALYSIS

The classification of objects into different groups sharing the same characteristics is termed as clustering. Clustering is a common technique for data mining, image analysis, biology and machine learning. Techniques which search for separating data in to convenient groups or clusters are termed as clustering analysis (Everitt, 1974). Most markets as well as customers are heterogeneous in their needs and preferences (Clarke, 2009). In industrial markets, suppliers must carefully consider the nature and characteristics of their customers in order to satisfy them (Hosseini et al., 2019). Segmentation as a technique for forming customer groups for effective targeting is a widely researched area in marketing (Branke et al., (eds) (2008)

Cluster analysis is a popular tool to segment markets. Simply stated, it is a technique for separation of customers into different groups such that each group of customers is

collectively different from the customers in the other groups. Many methods of cluster analysis are available in the literature. But on a broad basis, clustering techniques can be divided into two groups: classical (hard or deterministic) cluster analysis and probabilistic (fuzzy or soft) cluster analysis (Budayan, 2008). A number of studies carried out in different fields compare the performance of these two different clustering approaches (Budayan et al., 2008). In a majority of these comparison studies, fuzzy clustering is discussed as the most popular form that has been adopted in diverse fields, presumably because it adds valuable diagnostics over hard clustering (Ozer, 2001). A relatively unexplored field of soft clustering technique for market segmentation is known as probabilistic-D clustering (Branke et al., (eds) (2008).

Hard Cluster Analysis

The term - hard cluster|| analysis refers to all clustering techniques where the assignment of observations to cluster is deterministic. Stated differently, in hard clustering techniques each observation has 100% chance of belonging to one and only one cluster. There are two main groups of clustering methods, hierarchical and non-hierarchical clustering, each with many different sub-methods and algorithms. In agglomerative hierarchical methods, each observation is initially assigned to its own cluster and then merged with others based on a similarity measure. The algorithm continues until all data points form a single cluster solution. In non-hierarchical methods such as k-means, an iterative partitioning algorithm is used that does not impose a hierarchical structure (Budayan, 2008). We selected k-means, one of the most widely used clustering methods for segmentation, to compare with probabilistic-D clustering.

K-Means Cluster Analysis

The K-means cluster analysis is one of the most popular hard cluster analysis techniques (Blattberg et al. 2008). In a classic application of this technique, the number of clusters k must be pre-specified. The algorithm then selects cluster centers and each of the observations in the data is assigned to a particular cluster based upon the shortest Euclidean distance of the data point from the cluster centers. It is an iterative procedure; once observations are assigned to cluster centers, new cluster centers are created by averaging the observations assigned to a cluster. Distances from these new cluster centers are calculated for all observations, and the assignment of observations to clusters continues until a convergence criterion is satisfied (Freling et al., 2001). This method has a number of advantages, such as its ability to handle large amounts of data points, and its ability to work with compact clusters (Freling et al., 2001). However, it has

its own set of limitations as well, such as the variables must be commensurable (Blattberg et al. 2008), the number of clusters should be known beforehand, and it is sensitive to outliers and noise (Budayan, 2008). In recent years, algorithms have been developed for an automatic (multi-stage) way of selecting the number of clusters, the k in k-means.

Soft Cluster Analysis

The term —soft cluster|| analysis refers to all clustering techniques where assignment of observations to clusters is chance-based. In other words, in soft clustering techniques there is a chance that each observation could belong to any of the clusters. Thus, the probabilistic clustering technique assigns probabilities of cluster memberships to each observation; therefore, it is not deterministic. Soft clustering techniques overcome the limitation of forceful assignment of an observation to a single cluster and hence are more appealing in business situations where segments may not be clearly differentiable and may be overlapping in character (Freling et al., 2001). Fuzzy C means clustering is the most commonly known type of soft clustering. However, we discuss here a relatively new and a simpler method of soft clustering, as described below.

Probabilistic-D Cluster Analysis

As per Israel and Iyigun, (2008), in probabilistic-D (distance) clustering, given clusters, their centers, and the distances of data points from these centers, the probability of cluster membership at any point is assumed inversely proportional to the distance from the center of the cluster in question. The clustering criterion being used here is Euclidean distances. Fuzzy C Means (FCM) cluster analysis is the most well-known and widely researched technique in soft clustering (Mu et al., 2011). The main differences between FCM and probabilistic-D clustering is that while FCM determines the cluster centers as well as the distances between the cluster centers and observations simultaneously, in Probabilistic-D clustering the cluster centers are determined first. Then, based on those cluster centers, the distances (Euclidean) are calculated to assign probabilities of cluster membership. Our motivation to look for an approach other than FCM is as follows. First, FCM is known to be slow to converge, especially with large data sets (Freling et al., 2001). Second, in spite of our best efforts, we could not find a macro or algorithm to readily apply FCM using SAS®. Israel and Iyigun, (2008) argue that probabilistic-D clustering is simpler process, is robust and gives a higher percentage of correct classifications. From a SAS® user point of view, application of probabilistic-D clustering should be easier because it can be built upon the familiar k-means output by extracting the distances from

cluster centers and then using those distances to calculate the probabilities of cluster memberships.

12. CONCLUSION

This brief focused review has shown that there is a rich variety of approaches and solution methods used for disruption management in vehicle routing and scheduling. The area is ripe for future research to improve on existing methods and to provide even better decision support for those managing distribution operations using road vehicles. Technical developments that should be taken into account in devising new approaches include the following aspects: Quicker and better communications between drivers and management are now available to obtain timely and reliable information about the current status of the vehicle and to inform drivers of revised plans. This may allow additional time to build a revised plan.

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