APPLICATION OF VEHICLE ROUTING OPTIMIZATION IN IMPROVING THE FLOW OF MAIL TO A PROCESSING PLANT

Authors:
NIROOMAND Iman, KHATAIE Amir, FOOMANI Matin
Canada Post Network Design Department

Introduction

A Vehicle Routing Problem (VRP) involves pick-up/delivery tours generating on a network or its subsets in order to meet nodes, given a set of constraints and the need to optimize one or several fixed objectives. Network at postal services is represented as a graph on which nodes stand for customers, point of service, depot, sorting facilities while arcs stand for real links (i.e. road, rail and air services). Hence each arc has a traversing time and cost while time window and demand are associated factors to the nodes. This dynamic problem could get more sophisticated if several heterogeneous or homogenous fleet are involved at several periods.

This paper presents the results from of a practical application conducted on a subset of network for a target group of customers in the Greater Toronto Region (GTA) network. The rest of this paper will describes different approaches to metaheuristics method covered in literature followed by a nobble ACO method applied for GTA case and finally concludes the paper with remarks and an insight to future works.

Metaheuristics methodologies and approaches in VRP

After WWI and manifestation of Operational research techniques, it were widely applied to problems in business, industry and society. VRP is one of the most important and challenging optimization problems first introduced by Danrzing & Ramser in late 50's to find optimum routing of a fleet of gasoline delivery trucks between bulk terminal and service stations[1]. This subject has been intensively deliberate by numerous researchers in the past six decades and many models and methods has been proposed. However VRP is computationally hard combinatorial problem and there is a lot of room for improvement. VRP is originated from an ancestor model of Traveling Salesman Problem (TSP) and Multiple Traveling Salesman Problem (mTSP). Capacity based problems CVRP are more responsive to the nature of these problems. The principal is that the shortest tour to visit a number of customers having a specific location and size must be determined for an agent originating/ending up to a depot(s). However Finding the exact optimum solution for a large network is still a dream and limited to problems with couple of hundred customers [2]. Even though Mathematical modeling and programming are hired to formulate CVRP. leporte et. al. proposed a mixed integer linear programming to minimize minimum number of vehicles needed to serve the nodes [3], other studies are using Lagrangian Relaxation and duality in order to relax constraints and add them to the objective function [4]the goal has been set to find the exact optimum solution [5][6]. The objective on other studies was to identify a set of routes that form a feasible solution with minimum total cost[7]. The complexity of the CVRP problem falls under NP-hard in the complexity theory[8]. The challenge is to find a technique that can provide high-quality solutions, though not necessarily an optimal one, but an approximate solution within short or acceptable computational time.

Heuristic methods can fall under three categories; Constructive heuristics, improvement heuristics and more recently metaheuristic models [9]. Metaheuristic deployed based on concepts derived from artificial intelligence, biology, mathematics, physics or nature in order to obtain better solutions. The purpose of metaheuristic is to drive an acceptable extension from classic optimization techniques. Metaheuristic models are widely used on VRP [10] with deferent level of sophistication with multiple depots [11]or time window[12] or by deploying local search improvement techniques[13],[14]. These methods are categorized into three groups: local search algorithms, population search algorithms and learning mechanisms algorithms [15]. The latter group has the abilities of gripping knowledge gradually during the search procedure and generating new solutions. The ACO used to construct solution in this research is basically using the phenomenon that ants are using to fin shortest path from nest to food sources.

Artificial ants are creating different edges from source to sink. The edges selected in the good solutions are marked with artificial pheromone, which is used to guide the following ants[12] [16][17]. In the next section, first, we will describe Toronto postal plan processing and second, we will show how using ACO would help the postal logistic and transportation department to bring a decent portion of collected volume earlier to plant for processing.

Canada Post – GTA collection case:

The postal service network is consists of three floating layers; (1) customer collection by 3rd party including; consolidation and product segregation, (2) transportation and sort at different processing facilities with limited capacity and throughput across the network, and (3) sort at depots and delivery to customers by delivery agents. Hence it's vibrant, dynamic, and interconnected problem which makes it more complex than the traditional vehicle routing problems in the sense that decisions needed to be made at the sorting plant and these decisions required interaction between planning of pickup and delivery routes. The combination of volume, variety, variation of service and visibility is making it even harder [18].

Canada Post process approximately 100 million pieces of parcels in Toronto annually coming from differing sources such as retail network, international mail, other processing plants and online retail stores which accounts for more than 60% of the volume. Because of nature of online shopping there is a huge variation between days in terms of volume which has been processed. Collecting mail from such a network requires a sophisticated planning tool otherwise it can result lots of unscheduled services to absorb the volume variation and minimize its impact on the arrival time in the processing plant in order to protect service. While the volume is increasing such a model is not only reduces the transportation cost but also contributes to the better serviceability for highly committed products.

The customers can be divided to two groups based on their volume. The customers with sufficient volume to dispatch directly to the processing plant and the customers with smaller volume, small and medium business (SMB) which they will be served via a specific collection network. The focus of this study is on the second group of customers. In 2015, approximately 40 daily tours were visiting more than 400 commercial customers in GTA to transfer their volume to CPC plant in Mississauga. The historical data has revealed that the major volume received by CPC occurs during the hectic hours which put the plant under heavy processing pressure. The service is available between 10:00 to 23:00 while 45% of the volume arrives between 18:00-22:00. This also occurs during traffic rush hours. This issue was raising the risk of failure of Toronto main sort plant to meet the cut-off for parcels and packets and was causing a ripple mark effect downstream of the network.

The flow of volume to the processing plant was also highly dependent to the customers' pickup time window. A large portion of the SMB customers desired to have their volumes to be picked up after working hours to maximize their serviceability. Although this late pickup benefits the commercial businesses in the urban area but it has a major impact on CPC facilities performance. Another observation was the plant yard sizes limitation and number of docks available to accommodate arriving trucks induction. This issue was creating line-ups at processing plant during the rush hours. Moreover, this long wait time was creating a huge congestion at processing plant and causing committed products to not be processed on-time as expected before the cut-off. This situation was reducing the level of service remarkably at downstream.

The desire goal is to smooth down the flow of trucks to processing plant in order to improve throughput of processing at the plant. This goal helps to reduce the congestion and traffics during the peak hours and increases the plant utilization throughout off-peak and as consequence helps Toronto operations to meet the commitment with no extra investment on the plant capacity.

Methodological approach

The customers are grouped based on their product availability. In GTA this time slots could be grouped as morning hours (800 to 1200), after noon hours (1200-1600), and evening hours (1600 t0 1900). The routing schematic for each group is constructed by VRO using Ant Colony Optimization (ACO) technique [19]. The objective function of the model is defined as constructing the routes by minimizing total driven kilometre. The two main sets of constraints are defined as:

a. Visiting the customer locations during provided time window advised by customers
b. Volume constraints per truck capacity.

Optimization termination is set as 100 non-improvement consecutive solution. At each iteration, the agents (ants) starts from plant build up their routes according to amount of disposed pheromone from previous iteration and minimum travel distance between adjacent nodes. The selection of next visiting node is based on a random number generator (RNG) and compares it with the cumulative probability of each node. For example, if there are only 4 nodes left to be visited. Each node gets a specific probability according to its distance from current node and its pheromone value. If the probability density function of these Nodes comes as $P_n(0.05,0.55,0.25,0.15)$ then the cumulative distribution is $C_n(0.05,0.6,0.85,1)$. In the case of RNG=0.2 then second node would be next visited node.

After visiting all the nodes, the agents will be back to the base. The new total driven kilometre is compared with either initial value or previous iteration. In the case of improvement the current solution is stored and new pheromone value is updated on each network leg. The flowchart of solution methodology is shown in Figure 1.The model is run on 3.4 dual core Intel i7 processor with 16 GB RAM. The solution is converging after 45 minutes run.

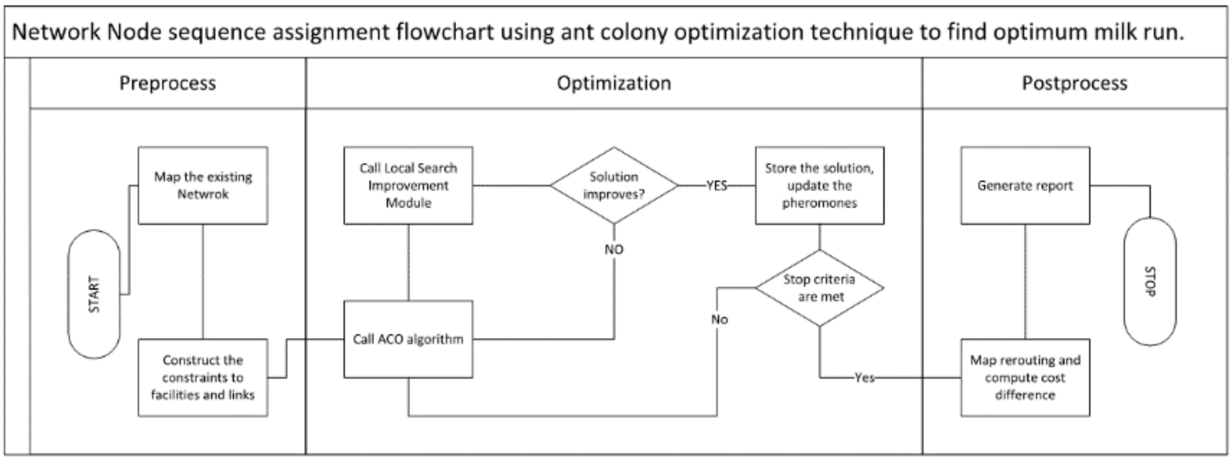
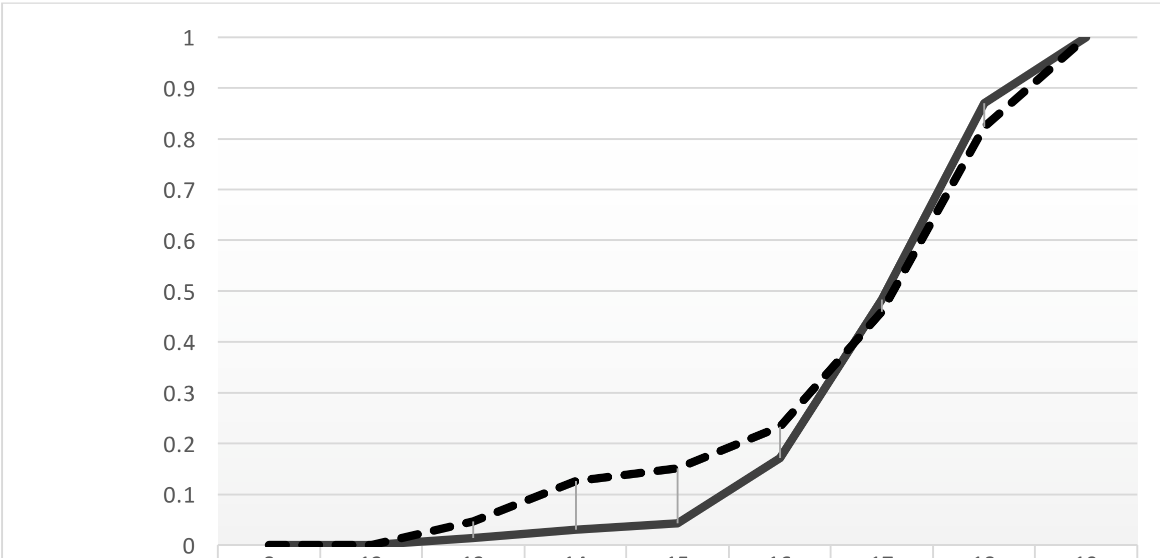


Figure 1- solution methodoloy for improving volume flow to processing plant

Computational Results

To further demonstrate the electiveness of the model, first the root cause(s) of the problem has been identified based on close observation of the failures. The next step was to select the causes for which an improvement must be adapted. The lack of capacity during the peak hour was highly correlated to the stream of returning trucks and as described earlier the SMB customer were clustered according to their proximity and location preferences. In the new described model, customers are firstly clustered based on their product availability and then the model delivers an optimized pickup sequence considering distance traveled. As the result of this new sequence the collected product brought back to the processing plant more evenly and earlier to be processed. Figure 2 is presenting the cumulative percentage of the volume inducted into the plant in 5 consecutive weeks, before and after the implementation of the model output.



	8	12	13	14	15	16	17	18	19
Before	0	0	0.0144665	0.0307414	0.0424955	0.1708861	0.4837251	0.8698011	1
After	0	0	0.0473062	0.1261498	0.151117	0.2325887	0.4599212	0.8239159	1

Figure 2 – volume early arrival percentage

The promising output is showing how the improvement in volume flow at Gateway plant has been relaxed. In a few weeks after implementation, about 40% of volume arrives before peak period which increased roughly 20% of serviceability.

Conclusion Remark

In a multi-stop collection network a change in a behaviour of one customer can cascade later arrival time and service failure on other customers. A tool is required to control the arrival time of the items to the processing facility which ultimately result protecting the service commitment. Such a tool should quickly evaluate and return a new solution upon the customers' behaviour changes, including volume and pickup time. Accordingly, Implementation of ACO for multiple-vehicle routing problem with short finish time is discussed in this paper. Conclusion emerges from the preceding works on deployment of ACO on learning mechanism and its potential in VRP has motivated us to apply this method on CPC dynamic VRP problem. The metaheuristic approach we deployed in order to make fast pace and responsive model had a remarkable impact in the results.

In addition, such a model establishes a performance evaluation system, since now there is an optimize scenario defined which the 3rd party performance can be compared with, especially in Canada Post pickup case which 3rd party runs a dedicated transportation network for the company. There is also an opportunity to extend this model and include a customer management tool in order to trace back the cost of customer behaviour changes on the collection process. For example, considering the fact that a customer who expect a later pickup time can be charged higher or the overall impact on the collection network of GTA can be quickly evaluated.

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