CHAPTER TWO

Literature Review

1. Engineering Fast Route Planning Algorithms:

Description of Problem***:*** Finding an optimal route in a transportation network between specified source and target nodes is one of the showpieces of real-world applications of algorithmic. We frequently use this functionality when planning trips with cars or public transportation. There are also many applications like logistic planning or traffic simulation that need to solve a huge number of shortest-path queries in transportation networks. The cost function may be any mix of travel time, distance, toll, energy consumption, scenic value associated with the edges. The task is to compute the costs of optimal paths between arbitrary source-target pairs.

Algorithms and Solutions:Dijkstra’s Algorithm (Dijkstra, E.W.,1959) - The classical algorithm for route planning- maintains an array of tentative distances D[u] ≥ d(s, u) for each node. The algorithm visits (or settles) the nodes of the road network in the order of their distance to the source node and maintains the invariant that D[u] = d(s, u) for visited nodes. We call the rank of node u in this order its Dijkstra rank rks(u). When a node u is visited, its outgoing edges (u,v) are relaxed, i.e., D[v] is set to min(D[v], d(s, u) + w(u,v)). Dijkstra’s algorithm terminates when the target node is visited. The size of the search space is O(n) and n/2 (nodes) on the average. We will assess the quality of route planning algorithms by looking at their speedup compared to Dijkstra’s algorithm, i.e., how many times faster they can compute shortest-path distances.

Priority QueuesDijkstra’s algorithm can be implemented using O(n) priority queue operations. In the comparison based model this leads to O(n log n) execution time. In other models of computation (e.g. Thorup, M.,2003) and on the average (Meyer, U.,2001), better bounds exist. However, in practice the impact of priority queues on performance for large road networks is rather limited since cache faults for accessing the graph are usually the main bottleneck. In addition, our experiments indicate that the impact of priority queue implementations diminishes with advanced speedup techniques since these techniques at the same time introduce additional overheads and dramatically reduce the queue sizes.

Bidirectional Search executes Dijkstra’s algorithm simultaneously forward from the source and backwards from the target. Once some node has been visited from both directions, the shortest path can be derived from the information already gathered (Dantzig, G.B,1962). In a road network, where search spaces will take a roughly circular shape, we can expect a speedup around two —one disk with radius d(s, t) has twice the area of two disks with half the radius. Bidirectional search is important since it can be combined with most other speedup techniques and, more importantly, because it is a necessary ingredient of the most efficient advanced techniques.

Geometric Goal Directed Search (A∗) The intuition behind goal directed search is that shortest paths ‘should’ lead in the general direction of the target. A∗ search (Hart et al.,1968) achieves this by modifying the weight of edge (u,v) to w(u,v) − π(u) + π(v) where π(v) is a lower bound on d(v,t). Note that this manipulation shortens edges that lead towards the target. Since the added and subtracted vertex potentials π(v) cancel along any path, this modification of edge weights preserves shortest paths. Moreover, as long as all edge weights remain nonnegative, Dijkstra’s algorithm can still be used. The classical way to use A∗ for route planning in road maps estimates d(v,t) based on the Euclidean distance between v and t and the average speed of the fastest road anywhere in the network. Since this is a very conservative estimation, the speedup for finding quickest routes is rather small. (Goldberg and Harrelson,2005) even report a slow-down of more than a factor of two since the search space is not significantly reduced but a considerable overhead is added.

Improving Operations with Route Optimization :

Description of Problem:Vehicle Routing Problem (VRP) can be described as the problem of creating a set of optimal routes from one, or many, depots to multiple customers, subject to a set of constraints. The objective is to deliver goods to all customers, at the same time minimising for the cost of the routes and the number of vehicles. Currently, the state-of-art solutions are obtained using the metaheuristics: (Nagata,2007) Genetic Algorithms, (Bräysy and Gendreau,2002)Tabu Search and (Tan et al.,2006)Ant Colony Optimization. These are the methods mainly used in the field nowadays.

Algorithms and Solutions: In the first version of our software, the volume of orders submitted to Route Optimizer quickly increased from 500 items per warehouse to 1000+. Theoretically, we should be fine. Our algorithm runtimes and memory usage jumped incredibly quickly from 1 minute and 500 MB to 10 minutes and 5 GB. As we tested it for higher and higher volumes, we finally reached the maximum for 2000 waypoints the module used up 25GB of RAM memory. That is why we decided to use a modified approach  called “recursive-DBSCAN”.

Recursive-DBSCAN; We decided to try (Ester et al.,1996) DBSCAN algorithm, at the same time the algorithm allows us to dig in deeper into high waypoint-density regions, while grouping remote orders together.

For a list of orders, we aim to find the radius for which the average number of waypoints will be the biggest (but the number of clusters will be higher than min\_no\_clusters). We do so by using a simple binary search algorithm.

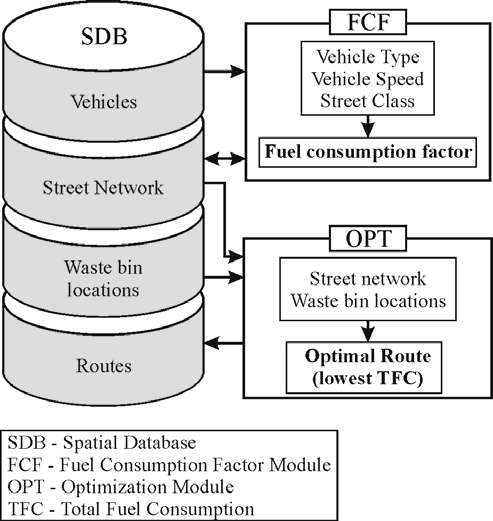
Once we have found the optimal solution we “enter” the clusters that are too big and apply the same logic until we reach a point when each cluster contains less than max\_len\_cluster. Then, for each cluster, we run Route Optimization algorithm we have developed using Google Optimization Tools. This method will give us a similar result more quickly, and using less RAM memory.

Multi-objective Genetic Algorithms for Vehicle Routing Problem with Time Windows :

To make for effective decision and comparisons of methodologies of route optimization problem, multi-objective optimization and pareto ranking applications of genetic algorithms were used to compare all items of route that contains customer information, many approach has been used, but genetic algorithm solution is more effective than other solution. In genetic algorithm, that must contain fitness function effectively. Genetic algorithm process replaces the fitness function by raw pareto ranks, using pareto ranking algorithm. Run the genetic algorithm successfully, the pareto front will be the set of solution obtained.In this solution, a chromosome representing a network configuration, is given by an integer string of length N that is the number of customers in particular problem instance. A gene in a given chromosome indicates the original node number assigned to a customer. A chromosome is like 2 5 1 4 7 8 6 3 9. (Hanshar et al.,2006)

Route Optimization To Increase Energy Efficiency and Reduce Fuel Consumption of Communal Vehicles :

Route optimization for minimal fuel consumptionIn generally, the route optimization first purpose is saving fuel consumption and time. This approach is using many criterion of distance, and expand that the existing database, and determine the optimal route for fuel-economical. This model is shown on figure 1. The figure contains street network, vehicles, routes, waste bin locations. Each streets are in between two junction of street segment. Each street segment was attributed with fuel-consumption factor ( fc ). The most fuel-economical route has the lowest Total Fuel Consumption (TFC) expressed by equation: TFC = Σ(Lsegi fci), where Lsegi presents the length of street segment with matched fci.(Bošković et al.,2010)

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*Figure 1 Approach Model*

Route optimization for solid waste collection :

This approach was used in waste collection problem. But this work contains many vehicle, and routes, of course route planning like our project. A shortest path model was used in order to optimize solid waste collection/hauling processes, by aiming at minimum distance. The Route View ProTM software integrated with GIS elements such as numerical pathways, demographic distribution, container distribution and solid waste production was used as an optimization tool. (Apaydin and Gonullu,2007)

An Effective Genetic Algorithm for Capacitated Vehicle Routing Problem :

The capacitated vehicle routing problem (CVRP), is one of the most important topic in operation cargo companies, making logistics, many little and big carriers. It is of paramount importance to thousands of companies and organizations engaged in the delivery and collection of goods or people. Metaheuristics techniques are often more suitable for CVRP to find a near optimal solution.

The CVRP is defined as an undirected graph 𝐺 = (𝑁,𝐸), where 𝑁 = {0, 1, … , 𝑛} is the set of nodes, 𝐸 = {(𝑖, 𝑗) ∶ 𝑖, 𝑗 ∈ 𝑁, 𝑖 ≠ 𝑗} is the set of edges joining the nodes. Node 0 is the depot and the other nodes represent the customers having a known demand 𝑑𝑖 for customer 𝑖. The travel distance between node 𝑖 and 𝑗 is defined by 𝑑𝑖𝑗 > 0 and each vehicle 𝑘 has a unique capacity of 𝑄k.

A discrete firefly algorithm to solve a rich vehicle routing problem modelling a newspaper distribution system with recycling policy :

This article contains vehicle routing problem modelling using Firefly algorithm, that was first developed by Xin-She Yang in 2008 (Fister et al. 2014). Firefly algorithm is generally using for solving continuous optimization problems. Here to calculate distance between two routes, Euclidean distance was used. But Firefly algorithm cannot be applied directly to solve the problem. We must modify the algorithm to find the best solution. The modify is in order to prepare it for addressing problem. At the same time the distance calculation of our problem can use the Hamming distance between two fireflies is the number of non-corresponding elements in the sequence. (Diaz et al. 2017)

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