Application of Genetic Algorithm to Solve Capacitated Vehicle Routing Problem With Time Windows and Non-Identical Fleet

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Abstract— we developed a solution method for solving the Capacitated Vehicle Routing Problem with Time Windows and Non-Identical Fleet (CVRPTWNIF). The problem is known to be computationally hard-to-solve. Consequently, there is no known algorithm that finds the optimal solution in a polynomial time function of number of delivery locations. Hence, we propose a solution method based on Genetic Algorithm. We solve randomly created data sets using the proposed method and compare the results with those obtained using a commercial software application. Our computational results illustrate the effectiveness of the proposed method in finding good solutions for the small-scale random problem instances.

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1 INTRODUCTION

The The Vehicle Routing Problem (VRP) has been studied as an important problem in logistics management.

A proper selection of vehicle routes is extremely significant for improving the economic benefits of logistic operations. The VRP is one of the difficult problems in Operations Research. It is a non-deterministic polynomial-time hard problem, which means that no polynomial-time algorithm is found yet for determining an optimal solution. This problem has many applications in real life. For example, equipment stores may use many trucks to deliver equipment to customers. To minimize transportation costs, the store may need to determine which truck route should service what orders (customer sites) and what sequence the sites should be visited. The objective is to find the best solution with satisfactory customer service at minimal overall operating cost. The VRP can include additional problem characteristics such as matching vehicle capacities with order amounts, providing a high level of customer service by honoring time windows on orders, giving breaks to drivers, and combining orders so that the same route can service both pickup and delivery of products.

(Laporte 1992).

Consider an example problem of delivering goods to grocery stores from a central warehouse location, where a fleet of five trucks is available. The warehouse operates only within a certain time window—from 6:00 a.m. to 6:00 p.m.—by the end of which all trucks must return to the warehouse. Each truck has a capacity of 13,000 pounds, which limits the load it can carry. Each store has a demand for a specific amount of goods (in pounds) that needs to be delivered, and each store has a time window that confines the deliveries. Furthermore, drivers can work only eight hours per day, require a break for lunch, and are paid for time spent on driving and servicing the stores (Laporte 1992). The VRP for this example can be described as finding the optimum route for the set of vehicles, which have limited capacity, travel time and service requirement for the customers. The VRP has many variants, for instance, the vehicle routing problem with time windows (VRPTW), the multi-depot vehicle routing problem (MDVRP), the capacitated vehicle routing problem (CVRP), the site dependent vehicle routing problem

(SDVRP), the open vehicle routing problem (OVRP), pickup and delivery vehicle routing problem (PDVRP), time-dependent vehicle routing problem (TVRP), and periodic vehicle routing problem (PVRP). While many researchers have studied these problems extensively, the well-studied cases are the VRPTW, PDVRP and CVRP.

Many researchers have focused on the development of meta-heuristic based solution techniques to obtain near-optimal solutions for VRP. Meta-heuristics are solution procedures that often embed construction and improvement procedures in exploring the solution space to identify good solutions. These include Genetic Algorithm (GA), Ant Colony Algorithm (ACA), and Particle Swarm Optimization (PSO). The GA has proven to be effective in solving the VRP. In the next section, we present a brief review of literature relevant to the VRP.2 Procedure for Paper Submission

2.1 LITERATURE REVIEW

Since the introduction of VRP by Dantzig and Ramser (1959), the problem has attracted many researchers in developing efficient algorithms for this problem. The solution methods for VRP include exact algorithms, heuristic search procedures and meta-heuristics. The heuristic search procedures aims to get an acceptable solution quickly, and subsequently improve the solution. Well-known meta-heuristics developed by researchers include the GA, Tabu Search, Sweep Algorithm, and Simulated Annealing, which are based on two main principles: local search and population search (Dantzig & Ramser 1959).

Tasan. et al (2012) proposed a GA based heuristic to solve PDVRP. This problem is an extension of the CVRPTW where a fleet of vehicles originates from a depot to serve customers with the consideration for reverse logistics activities. The proposed GA algorithm was applied to solve a numerical example for illustration purposes. Niazy and

Badr (2012) studied the utilization of the Cellular Genetic Algorithm (CGA) in solving the CVRPTW with the goal of minimizing the total distances traversed. CGA is a subclass of GA where the population range and exploration are enhanced (Niazy & Badr, 2012). They compare the behavior of the algorithm in contrast to the solution quality, implementation time and iteration. Their study shows that the CGA is capable of consistently finding good solutions to the CVRPTW in an reasonable time. In addition, they concluded that, CGA is capable of finding a solution to most CVRPTW instances with lesser number of iterations but with lower hit rate in finding optimal solutions.

Khoshbakht & Sedighpour (2011) and Lopes et al (2010) proposed an ant colony algorithm (ACA) for solving the CVRPTW. They modify ACA pheromone evaluation method in such a way that it can avoid premature convergence for improving the algorithm's performance.

2.2 THE DESCRIPTION OF CAPACITATED VEHICLE ROUTING PROBLEM WITH TIME WINDOWS AND NON-IDENTICAL FLEET (CVRPTWNIF)

The objective of the CVRPTWNIF is to minimize the total cost of routing while ensuring customer satisfaction. In addition, the weight capacity of the vehicles must not be exceeded by the weight range of the total number of customer orders served by the vehicle. Each vehicle originates from a depot, serves the customers at known locations, and returns to the depot. The routing problem is characterized as follows:

1. The objective of the problem is to reduce the total cost of routing that includes a fixed cost for dispatch and a variable mileage cost component.

2. A known number of vehicles originate from a depot

3. Each vehicle serves a subset of customers and returns to the depot

4. The total customer demand served by a vehicle must not exceed the vehicle's capacity

5. All customers are served by a vehicle, exactly once

6. The set of vehicles are not necessarily identical in their capacity, average speed of travel, and mileage cost and dispatch cost.

2.3 Solution Approach Using the Genetic Algorithm

The idea behind the GA is to simulate the survival of the fittest among solutions over consecutive generations of solutions, which is applied to solve an optimization problem. Each generation consists of a population of character strings that are analogous to the chromosome in human DNA. Each chromosome represents a point in the search space and a possible solution for an optimization problem (J.E. Rawlins, 1991). We propose a GA based method for solving the CVRPTWNIF with the following steps.

A. Solution encoding
B. Fitness function development
C. Initial population generation
D. Crossover operation
E. Mutation operation

We briefly explain the steps of the proposed GA and we will illustrate a numerical example in next section.

A. Solution encoding

In GA, it is very critical to represent solutions as chromosomes. We encode a solution to the CVRPTWNIF, which is a sequence of delivery locations, as a string of integer valued chromosomes. In addition, we also represent the sequence of non-identical trucks as a string of integer valued chromosomes. Consequently, we maintain two parts in a chromosome, where the first part corresponds to the sequence of delivery locations and the second part corresponds to the sequence of non-identical trucks.

B. Fitness function development

The cost of each route depends on the distance traversed in the route. Given a chromosome with two parts, we compute the fitness value as follows:

1- Initialize the first route with the first truck in the truck sequence and the first location in the sequence of customer locations, then compute the route weight for each vehicle and represent that as [k]. Next, initialize the departure time at depot to zero customer location. Then, compute the arrival time and represent that as $[t_n]$ for each location where n is the customer location.

2- Check if the truck route and the capacity of the truck is able to meet the customer requirements and the time windows by the following steps without violating the time and weight capacity constraints:

Step 1: Set t [i] = t [last location j visited in route k] + (distance [j][i]/AvgSpeed) and

- t [n] = t [i] + (Distance [i] [N]/AvgSpeed)
- Add the current customer to the current route and go to step 5,
- Else Set k = k + 1 and go to Step 2.

Where:

t [i] = represent the truck time for the location i

t [n] = represent the truck time from the location n

k = represent the route weight

v = represent the capacity of the truck

L= represent truck usage cost

Step 2: If k>v, then "infeasible Route Construction!" Stop!

- Else, go to Step 1

Step 3: If all customers are routed then construction is complete, go to Step 4,

- Else Set I to the next customer in the sequence SEQ [n+1], set k=1, and go to Step 1.

Step 4: Complete the routes by adding the depot as the last location.

Step 5: Compute the total mileage cost for each routes.

Step 6: Based on the number of trucks L used to serve the customer to compute the Truck usage cost.

Step 7: Add the mileage cost and the truck dispatch costs to obtain the total of vehicle routing cost.

C. Initial Population Generation

The choice of the initial population has a significant impact on the entire search process. The initial population is generated randomly and numbers are assigned to each location. One technique that implemented in heuristic is the randomized construction. In randomized construction, we create a random combination for the variable, then, we check the feasibility with respect to the capacity and obtain the objective value for each size, finally, we choose the solution with the best objective value and output that solution.

E. Crossover Operation

Crossover operator is utilized to generate new offspring by using two chromosomes. We randomly choose two chromosomes from the populations for the crossover and we create a random break point to perform a crossover.

F. Mutation Operation

In the algorithm, the mutation includes random change in the new crossed over chromosomes. As the mutation depends on the encoding. Mutation is implemented by exchanging two genes in the same chromosome. Two random locations or trucks are chosen be exchanged in the same

chromosome.

3   EXPERIMENTATION USING A C++ IMPLEMENTATION OF THE PROPOSED GA

We implemented the proposed GA using the Microsoft Visual C++ software. The performance of the GA was evaluated by comparing the run times of the best-known solutions with that of an implementation of a Mixed Integer Linear Program developed by Easwaran (2013). For the purpose of experimentation, we created five random instances.

4   COMPUTATIONAL RESULTS

The GA was solved by using the VC++ implementations while the Mixed Integer Linear Program (MILP) was solved using the IBM ILOG CPLEX 12.5, commercial optimization software. we summarize the results of five problem instances, including the total cost of the best known solutions determined by the two methods, the solution run times and the optimality gap. We observed that the GA was able to find the optimal solutions for all the five instances, as observed from the optimality gaps. However, the run time for the MILP was lower than that of the GA, but was very close. Consequently, we conclude that the proposed method works well for small-scale problems.

5   CONCLUSION

In this project, we studied the Capacitated Vehicle Routing Problem with Time Windows and Non-Identical Fleet (CVRPTWNIF). A proper selection of vehicles and design of routes are extremely significant for improving the economic benefits of logistic operations. We proposed a Genetic Algorithm (GA) based solution approach to determine feasible solutions to the problem, since the problem is known to be NP-hard. We presented numerical illustration

of the GA for a small problem instance and preformed computational experimentation using an implementation in Visual C++ programming language. We generated five random instances and performed the computational experiments for comparing the results of the proposed GA with the performance of the MILP solved using ILOG CPLEX 12.5. We observed that the GA was able to find the optimal solutions for the small-scale problem instances. The MILP, while capable of solving small-scale instances to optimality, may not solve large-scale instances to optimality, in reasonable time. Consequently, we may have to rely on metaheuristics for solving large-scale problems, such as the proposed GA to determine feasible solutions rather than optimal solutions. For the future research, recommend the proposed GA to be tested on large-scale problem instances.

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