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A HYBRID SEARCH BASED ON GENETIC ALGORITHMS AND TABU SEARCH FOR VEHICLE ROUTING

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ABSTRACT
We present a hybrid search technique based on meta-heuristics for approximately solving the vehicle routing problem with time windows (VRPTW). The approach is two phased; a global customer clustering phase based on genetic algorithms (GAs) and a post-optimization local search technique based on tabu search (TS). We also devise a new crossover operator for the VRPTW and compare its performance with two well-known crossover operators for VRPTW and related problems. Computational experiments show that the GA is effective in setting the number of vehicles to be used while the tabu search is better suited for reducing the total number of distance traveled by the vehicles. Through our simulations, we conclude that the hybrid search technique is more suitable for the multi-objective optimization for the VRPTW than applying either the GA or tabu search independently.

KEY WORDS
genetic algorithms, tabu search, meta-heuristic, Vehicle routing problem, combinatorial optimization

1 Introduction

Vehicle routing problems have received much attention in recent years due to their wide applicability and economic importance in determining efficient distribution strategies to reduce operational costs in distribution systems. As a result variants of it have been studied extensively in literature (for a detailed review, see Solomon and Desrosiers [1]). Practical examples of this problem include bus routing, mail and newspaper delivery, airline and railway fleeting and scheduling, industrial refuse collection [1].

A typical vehicle routing problem (VRP) can be stated as follows: the problem of designing least cost routes from one depot to a set of geographically dispersed points (customers, stores, schools, cities, warehouses etc) with demands [2]. Each customer is visited exactly once by only one vehicle with limited capacity. The VRPTW is a generalization of the vehicle routing problem (VRP), where each customer has a load that must be picked or delivered within a given time window. The objective is to find a set of least cost routes for the vehicles that serves a subset of the customers without violating the capacity and time window constraints, while minimizing the total distance traveled and the number of vehicles employed.

The VRPTW is a classical example of NP-complete multi-objective optimization problems. The combinatorial explosion is obvious and finding exact optimal solutions for these type of problems within reasonable time is computationary intractable [3].

Various researchers have investigated the VRP using various techniques and reported some interesting results [2][4-8]. Meta-heuristics have shown to give good solutions that we are satisfied with, even though they are not guaranteed to be optimal. Genetic algorithms [9-10], tabu search [11] and simulated annealing [7] are some of the well-known meta-heuristic techniques applicable to complex combinatorial optimization problems. GA is an application area that emerged from computer modeling of biological evolution [9]. Some of the attractive features of GAs include their robustness and their ability to search large, complicated and unpredictable search spaces.

Some researchers have investigated the application of tabu search for the VRP [7]. Tabu search (TS) is a local search meta-heuristic which relies on specialized memory structures to avoid entrapment in local minima and achieve an effective balance of intensification and diversification. In contrast to genetic algorithms, TS starts with a single solution (which need not be valid) and iteratively improve upon it by exploring the *neighborhood* of states that can be reached by applying an operator to the current state.

As a major contribution of this paper, we propose a hybrid search technique suitable for multi-objective optimization in VRPTW. Our approach is two phased; a global customer clustering phase based on genetic algorithm and a post-optimization local search technique based on tabu search.

The remainder of this paper is constructed as follows. Section 2 describes the problem definition. In Section 3 our proposed GA is presented and a comparison is done with the tabu search approach. Section 4 presents the implementation of hybrid search, based on GA and Tabu search. The concluding remarks are given in Section 5.

2 Vehicle Routing Problem with Time Windows:VRPTW

We adopt the problem definition given in reference [2]. The VRPTW consists of a set of identical vehicles V, which should service a set of geographically dispersed customers, C. For each customer, the service must be within a given time window, ot_i, ct_i. ot_i and ct_i are the opening and closing times for i, i belongs to C. Vehicles must leave the depot within the time window and return in the time window. A vehicle may arrive before the beginning of the time window and wait at no cost until service is possible. However, no vehicle may arrive past the closure of a given time interval. The objective function states that costs should be minimized. In this case the objective is to minimize the number of vehicles used and the distance traveled to meet the demand of all the customers while not exceeding capacity of the vehicle and the latest time for serving each customer. Thus this problem can be treated as a multi-objective optimization problem. For simplicity and space limitations, we leave out the mathematical modeling of this problem.

3 Routing Scheme Based on GA and Tabu Search

We carry out computational experiments to investigate a routing scheme based on GA and tabu search independently. First, we discuss the proposed GA method. In the GA, each chromosome in the population pool is transformed into a cluster of routes. The chromosomes are then subjected to an iterative evolutionary process until a minimum possible number of clusters is attained or the termination condition is met. The transformation process is achieved by our routing scheme whereas the evolutionary part is carried out like in ordinary GAs, that is, in each generation, genetic operations, crossover and selection are applied upon chromosomes. A problem-specific crossover operator is also devised for the VRPTW and its performance compared with that of uniform order crossover (UOX) [10] and partially mapped crossover (PMX) [10].

(1) Chromosome Representation

In order to apply a GA to a particular problem, we need to design a chromosomal representation for the solution space. We represent each chromosome as sequence of cluster of routes. A route is composed of a sequence of nodes (customers). For example, the chromosome:1 5 2 4 3 is composed of two routes r1:D C1 C5 C2 D and r2:D C4 C3 D. The correspondence between a chromosome and the routes is further explained in Section 3.1

(2) Evaluation of Chromosome Fitness

Since each chromosome represent a possible solution for the VRPTW, we determine the fitness of a chromosome after building the best possible cluster of routes from it in a given generation. In this paper, the fitness of an individual $F(x)$ is returned as;

$$Fitness = \alpha \cdot \mid V \mid + \beta \cdot \sum_{k \in V} D_k + \gamma \cdot \mid no\_service \mid \quad (1)$$

$$D_k = \sum_{i \in N} \sum_{j \in N} t_{ij} x_{ijk} \quad (2)$$

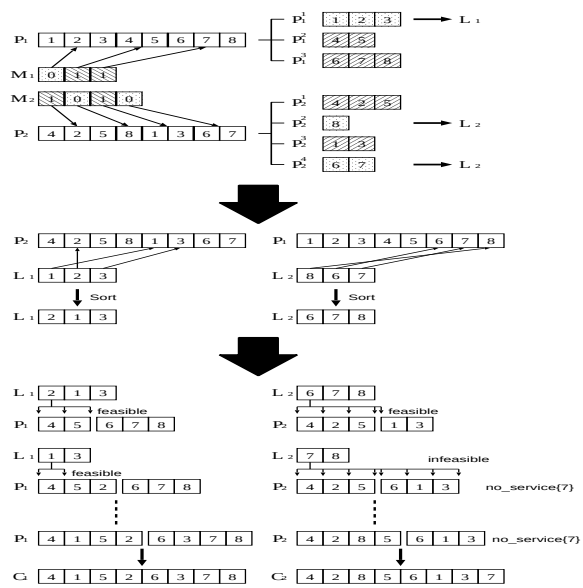
α, β, γ are weight parameters associated with the number of vehicles, total distance traveled by vehicles and the number of vehicles not serviced respectively. Since one of the main objectives is to service all customers, a chromosome that results in non-serviced vehicles is penalized accordingly by adding the penalty value, $\gamma \cdot \mid no\_service \mid$ to its fitness value. The weight values of the parameters used in this function were established empirically and set at $\alpha = 1.0, \beta = 0.001, \gamma = 1.0$. The evaluation function is carried out after applying the routing scheme given in [13] that converts each of the chromosomes into a cluster of feasible routes.

(3) Reproduction

Roulette wheel selection is used to generate a new population for the next generation. An elite model is incorporated to ensure that the best individual is carried on into the next generation.

(4) Proposed crossover operator

The the dynamics of the proposed RouteCrossover (RC) are presented here. RC is an improvement of the uniform order crossover [10]. Like the standard UOX, a randomly generated binary mask-pattern is generated. However, in the traditional UOX the length of a mask pattern is equal to that the mating parents is generating. Besides, in the UOX each bit of the mask-pattern has a one-to-one correspondence with each gene of the respective mating parents. However, in the RC, one bit of the mask pattern corresponds to one route in the respective chromosome.



Example 1: RouteCrossover (RC) Operator

Thus, in RC, the length of the mask pattern is equal to the number of routes represented in a mating parent (i.e., chromosome). Since the number of routes for two mating chromosomes may not necessarily be the same, two mask patterns are generated, one for each parent. Example 1 below depicts the creation of two offsprings using the Route-Crossover.

Example 1 illustrates the creation for two offsprings, C1 and C2, from two parents, P1 and P2, using an arbitrary problem instance of customer size 8, for explanation purposes. For every one route (consisting of genes representing customers) on a chromosome to be crossed, a "0" or "1" is randomly assigned, making a 0-1 mask pattern of length equal to the number of routes in the chromosome. In the Example 1 above, a 0-1 mask pattern of length three is given for parent, P1 since it has three routes, i.e., 1,2,3, 4,5 and 6,7,8 as shown in the Figure . Parent P2 has a mask pattern of length four respectively. Next, the contents of the route (s) corresponding to a "1" in the mask pattern is copied directly to their respective offsprings. The customers of the routes equivalent to "0" in the mask pattern are sorted out to form a list in order of appearance in their crossing parents. For example here, list, L_1, is generated by rearranging the order of appearance of 1,2,3 of P1, in P2. Using this list, each of the customers from the list is inserted according to their order of appearance to the first feasible position in the upcoming route represented by its respective offspring. However, this insertion is only done while checking feasibility constraints. Any customer that does not satisfy all the given constraints is declared as a non-serviced customer and is not assigned to any route.

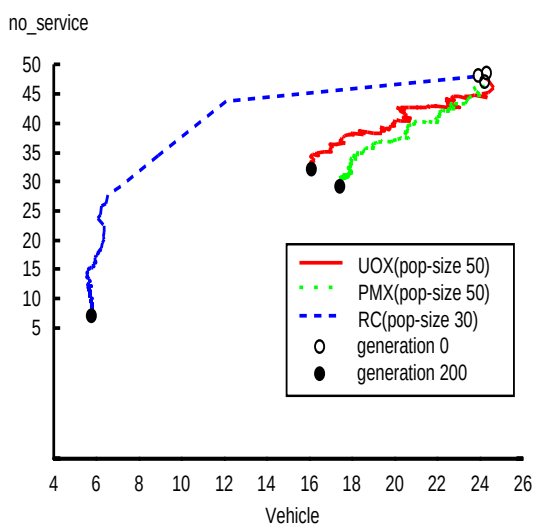


Figure 1. Comparing Crossover operators in minimizing No. of vehicles

3.1 Routing Scheme

We implement a simple routing scheme that transforms each of the chromosomes into a cluster of routes. A vehicle must depart from the depot and the first gene of a chromosome indicates the first customer the vehicle is to service. A customer is appended to the current route in the order that he/she appears on the chromosome. The routing procedure takes into consideration that the vehicle capacity and time window constraints are not violated before adding a customer to the current route. A new route is initiated every time a customer is encountered that cannot be appended to the current route due to constraints violation. This process is continued until each customer has been assigned to exactly one route.

3.2 Experimental evaluation of the GA

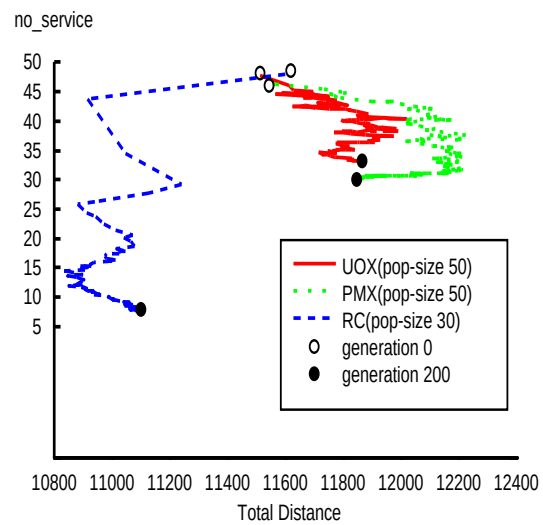


Figure 2. Comparing Crossover operators in minimizing distance

Computational experiments were carried out to investigate the performance of the proposed GA. Even though we show the results of only one problem instance, we used benchmark instances for the VRPTW available from the OR Library [12] web site. The performance of the proposed GA with respect to the minimization of the number of vehicles employed and the total distance traveled was under investigation.

The results provided by the graph given in Figures 1 and 2 were based on the following set of GA parameters:

1. population size = 30, 50
2. generation span = 200
3. crossover rate = 1.0

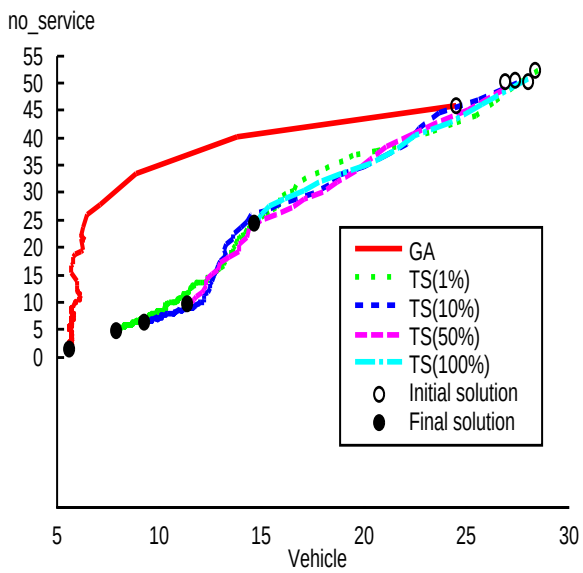


Figure 3. GA Vs Tabu search for Minimizing vehicles

Figure 1 shows performance of the GA when considering the number of vehicles as the main objectives while Figure 2 considers total distance traveled as the main objective. That is, in Figure 1, the GA tries to minimize the number of vehicles employed as much as possible. Likewise, in Figure 2, the GA tries to to reduce the distance traveled. The vertical axis in both Figures 1 and 2 show the number of customers not served. An ideal situation is when all the customers have been served.

To evaluate the effectiveness of the proposed Route-Crossover, we compared its performance with that of a GA using UOX [10] and PMX [10] respectively. From Figures 1 and 2 we observe that the RC outperforms that of the UOX and PMX. That is, the GA with RouteCrossover outperforms the one using UOX and PMX in reducing both the number of vehicles used and distance traveled. This observation is reported in all problem instances considered. Nevertheless, the performance of UOX versus PMX is problem instance dependent.

To further evaluate the performance of the GA, its performance is compared with that of the tabu search as explained next.

3.3 Tabu Search

Due to space limitations, we assume that the reader is familiar with with the basic principles of Tabu search [11]. Tabu Search (TS) works on a single solution at a step, although it always keeps a record of the best solution found. In exploring the neighborhood of a solution TS evaluates all the moves in a candidate list. The number of moves examined is one parameter of the search. The best move in the candidate list is generally accepted, unless the same move or its inverse has been made recently in which case it is taboo. Variations exist within the TS technique but mostly they all involve an interplay between the complementary pressures of *intensification* - selecting moves which improve the cost of the solution, and *diversification* - accepting non-improving moves in order to escape local optima.

TS can take a large computation time because of evaluations of all the moves. So we investigate how to reduce the neighborhood size in order to find an optimal or near optimal solution within a shorter time. We consider the cases of neighbor sizes of 1,10,50, and 100 percentages. Due to space limitations here, we limit our presented results only to those in comparison with the GA as shown in graphs in the next sub-sections. Generally we observed that when considering fitness versus Time (in secs), neighbor size of 1 percent generates a better solution than the others. However, in the case of fitness versus the number of steps, the search of 100 percent neighbor size is best while that of 1 percent is the worst.

3.4 Comparison of the proposed GA and TS

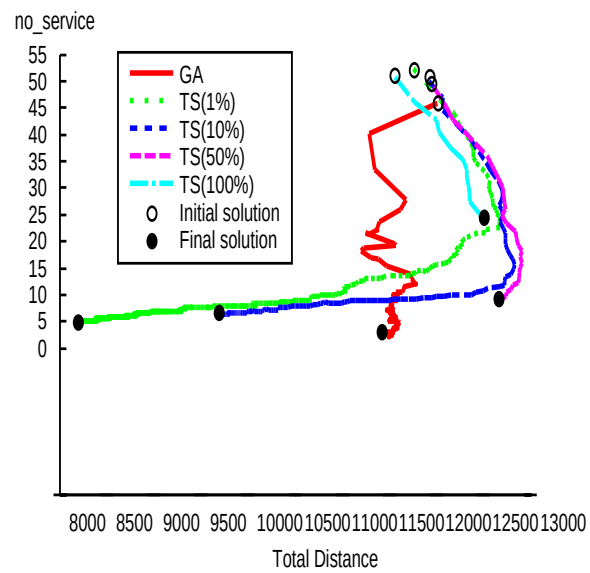


Figure 4. GA Vs Tabu search for Minimizing distance

Figure 3 and Figure 4 depict the performance of the genetic algorithm compared to that of the tabu search technique. In the case of Figure 3, the main objective under scrutiny is how the GA and tabu search performs respectively in defining the final number of vehicles to be used to service the customers for the VRPTW problem. Likewise, Figure 4 demonstrates their performance when the main objective observation is to minimize distance distance traveled. The vertical axis in both Figures 3 and 4 show the number of customers not served. The more the customers served the better. From Figure 3 we observe that GA per-

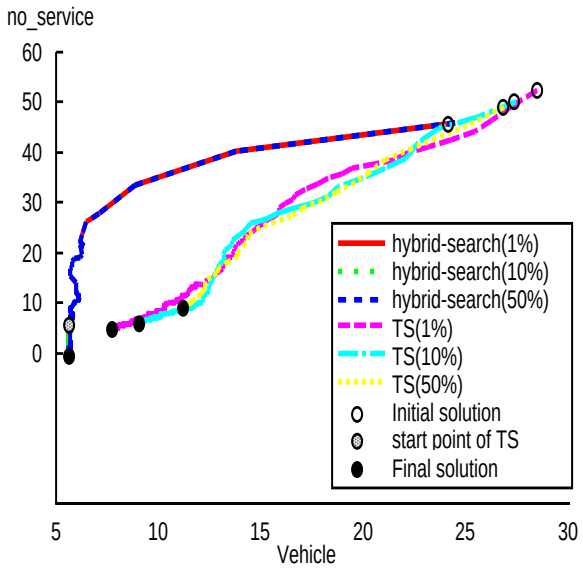


Figure 5. Hybrid search for Minimizing vehicles

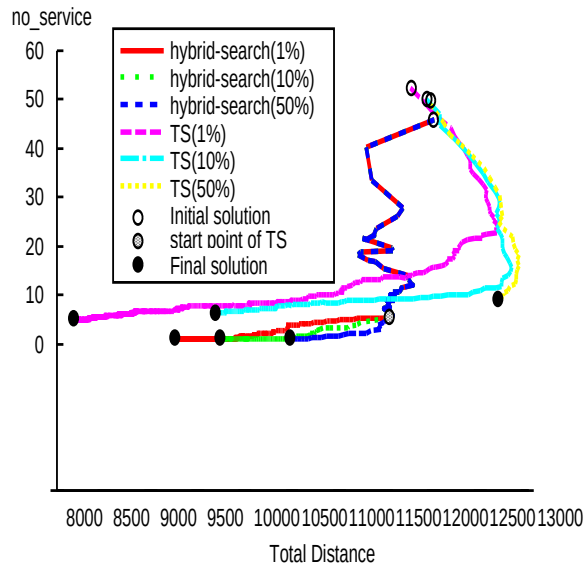


Figure 6. Hybrid search for Minimizing distance

forms better than the tabu search in searching the "optimal" number of vehicles to service the customers. As the figure shows, the GA manages to employ a smaller number of vehicles and also to serve more customers than the tabu search approach.

On the other hand, Figure 4 depicts that the tabu search outperforms the GA when it comes to minimizing the total distance traveled. Clearly, this a case of conflicting objectives. In-order to reduce the traveled distance, one would need to increase the number of vehicles. On the other hand, to reduce the cost of employing more vehicles, one needs to increase the distance traveled per vehicle (which does not necessarily solve the problem as the cost of gas and other resources comes into play as well).

From the results presented thus far, whether one chooses to use the GA or tabu search for the VRPTW depends on whether the individual's main objective of interest is determine the minimum number of vehicles to employ or reduce the amount of distance traveled per a given vehicle. However, a multi-objective search strategy that tries to strike a balance between the two main objectives would hopefully more efficient and thus we investigate it in the next section. The trade off between reducing the number of vehicles used and the total distance traveled is obvious and thus striking a feasible balance is necessary.

4 Two-Phased hybrid search for the VRPT

In this section we present a two phased approach for the VRPTW; a global customer clustering phase based on genetic algorithm and a post-optimization local search technique based on tabu search. The GA proposed in Section 3 is first applied on a given set of chromosomes for a number of generations followed by the tabu search. Computational experiments were carried out to evaluate the performance of the hybrid search by using the same benchmark problem instances discussed in Section 3. The same GA parameters as those given in Section 3 were also employed. For the tabu search, different neighborhood size bounds were investigated. Typical example of the results of this investigation are shown as in Figures 5 and 6 respectively.

The vertical axis in both Figures 5 and 6 show the number of customers not served. In Figure 5, the main objective under consideration is to determine the number of vehicles used (and preferably reduce the number as much as possible). We observe that the GA does a great deal in reducing the number of vehicles used and thus the Tabu search only makes some further improvement. When considering Figure 6 (where minimization of the total distance has higher weight as the objective), we note that after applying the GA, the Tabu search does a considerable reduction of the total distance traveled. From this observation, we can say that the GA is effective in setting the number of vehicles to be used while the tabu search is more effective in reducing the total number of distance traveled by the vehicles. Thus, applying a hybrid search that employs both the GA and tabu search is more suited for the multi-objective search for the VRPTW than employing each of the two meta-heuristics independently.

5 Concluding Remarks

We introduced a GA approach with a problem specific crossover operator suitable for VRPTW and other related problems. Emprical study showed that this crossover operator outperforms two well-known crossover operators ap-

plicable to the VRP and similar problems. To further improve on this strategy a more effective two-phased multi-objective hybrid search for the VRPTW was proposed. This was composed of a global customer clustering phase based on genetic algorithm and a post-optimization local search technique based on tabu search. We observed that the GA is effective in setting the number of vehicles to be used while the tabu search is more effective in reducing the total distance traveled by the vehicles. Thus the hybrid search technique is more more suitable for the multi-objective optimization for the VRPTW than applying either the GA or TS independently.

As a further extension on the vehicle routing problem, we will develop a flexible On-line heuristic search solution that is capable of dealing with sudden dynamic changes in the environment, taking into account of issues such as a sudden increase of customer size, vehicle breakdown and so on. This approach will incorporate cooperation criterion of meta-heuristics in distributed environments.

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